THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Smart Maintenance

- maintenance in digitalised manufacturing

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ABSTRACT

What does digitalised manufacturing entail for maintenance organizations? This is a pressing question for practitioners and scholars within industrial maintenance management who are trying to figure out the best ways for responding to the rapid advancement of digital technologies. As technology moves faster than ever before, this is an urgent matter of uttermost importance. Specifically, in order to secure the success of highly automated, intelligent, connected and responsive production systems, industrial maintenance organizations need to transform to become leading enablers of high performance manufacturing in digitalised environments. In this thesis, this transformation is referred to as "Smart Maintenance".

The purpose of this thesis is to ensure high performance manufacturing in digitalised environments by enabling the adoption of Smart Maintenance. In order to stimulate adoption, a holistic understanding of Smart Maintenance is needed. Therefore, the aim of this thesis is to describe *future scenarios* for maintenance in digitalised manufacturing as well as to *conceptualize* and *operationalize* Smart Maintenance. The holistic understanding has been achieved through a phenomenon-driven research approach consisting of three empirical studies using multiple methods.

Potential changes for maintenance organizations in digitalised manufacturing are described in 34 projections for the year 2030. From these projections, eight probable scenarios are developed that describe the most probable future for maintenance organizations. In addition, three wildcard scenarios describe eventualities that are less probable, but which could have large impacts. These scenarios serve as input to the long-term strategic development of maintenance organizations.

Smart Maintenance is defined as "an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies" and has four core dimensions: *data-driven decision-making, human capital resource, internal integration* and *external integration*. Manufacturing plants adopting Smart Maintenance are likely to face implementation issues related to change, investments and interfaces, but the rewards are improved performance along multiple dimensions when internal and external fit have been achieved.

Smart Maintenance is operationalized by means of an empirical measurement instrument. The instrument consists of a set of questionnaire items that measure the four dimensions of Smart Maintenance. It can be used by practitioners to assess, benchmark and longitudinally evaluate Smart Maintenance in their organization, and it can be used by researchers to study how Smart Maintenance impacts performance.

This thesis has the potential to have a profound impact on the practice of industrial maintenance management. The scenarios described allow managers to see the bigger picture of digitalisation and consider changes that they might otherwise ignore. The rich, understandable, and action-inspiring conceptualization of Smart Maintenance brings clarity to practitioners and policy-makers, supporting them in developing implementation strategies and initiatives to elevate the use of Smart Maintenance. The measurement instrument makes it possible to measure the adoption of Smart Maintenance in manufacturing plants, which serves to develop evidence-based strategies for successful implementation. Taken together, the holistic understanding achieved in this thesis enables the adoption of Smart Maintenance, thereby ensuring high performance manufacturing in digitalised environments.

Keywords: maintenance; manufacturing; digitalisation; industry 4.0; production system

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Trust is necessary for academic success. Without my supervisor Dr. Anders Skoogh, this thesis would not exist. You are the single most important enabler of the best pieces of research presented in this thesis. You have allowed me to take chances, go my own way, and always believed in my abilities and ideas. For this I am forever grateful. Thank you, Anders.

I also wish to thank Dr. Cecilia Berlin and Prof. Johan Stahre, who have always provided me with measured, thoughtful and useful advice. My research has benefited greatly from this. Together with Anders, Cecilia and Johan, I would also like to thank Dr. Thorsten Wuest for all your contributions to the appended papers.

These five years have been an absolute treat, largely thanks to my colleagues at the department. There are too many to name – but you have all contributed to creating the most inspiring, encouraging and heart-warming work environment imaginable for a doctoral student. We all become better researchers by both helping and questioning each other.

The research presented in this thesis is by no means a one man show. It reflects the minds of hundreds of industrial contributors and collaborators over the course of many years. Without the time, effort and vested interest from this large pool of people, there would be no data to analyse, no conclusions to draw and no thesis to read. As a researcher, I have been immensely privileged to collaborate with so many experienced, skilled and wise industrial experts. There are simply too many people to thank individually, but you know who you are. Thank you all.

Heartfelt thanks go to my family for your support in times of both the absence and presence of success. No one becomes a Doctor of Philosophy without going through some rough patches, but nothing feels better than celebrating this achievement together with you. Finally, I would never have managed the mental challenges of scholarship without all my friends on wheels and feet. Nothing takes your mind off things like pushing yourself to the limits. Maximum heart rate makes you wise.

Jon Bokrantz
Gothenburg, November 2019

APPENDED PUBLICATIONS

The following four papers are appended to this thesis (paper A-D).

Paper A. Bokrantz, J., Skoogh, A., Berlin, C., & Stahre, J. (2017). *Maintenance in digitalised manufacturing: Delphi-based scenarios for 2030*. International Journal of Production Economics, vol. 191, pp. 154-169.

Paper B. Bokrantz, J., Skoogh, A., Berlin, C., Wuest, T & Stahre, J. (2019). *Smart Maintenance: an empirically grounded conceptualization*. Under second review in International Journal of Production Economics.

Paper C. Bokrantz, J., Skoogh, A., Berlin, C., Wuest, T & Stahre, J. (2019). *Smart Maintenance: a research agenda for industrial maintenance management*. Under second review in International Journal of Production Economics.

Paper D. Bokrantz, J., Skoogh, A., Berlin, C., & Stahre, J. (2019). *Smart Maintenance: instrument development, content validation and an empirical pilot.* Submitted to journal.

WORK DISTRIBUTION

The distribution of work among the authors of each appended paper is in accordance with the following.

Paper A. Jon Bokrantz designed the study and conducted the academic focus group, interviews and literature review. Moreover, Jon developed the 34 projections and conducted the Delphi-study. He also performed data analysis, developed the scenarios and wrote the paper. Anders Skoogh conducted the industrial focus groups, assisted in developing projections, and contributed by reviewing the paper. Cecilia Berlin contributed to planning the focus groups and interviews, assisted in developing projections, created graphical illustrations, and reviewed the paper. Johan Stahre reviewed the paper and provided comments and advice.

Paper B. Jon Bokrantz designed the study and conducted the focus groups and interviews. Furthermore, Jon performed data analysis, developed the definitions of Smart Maintenance, modelled the Smart Maintenance concept structure, and wrote the paper. Anders Skoogh contributed to planning the focus groups and interviews, and reviewed the paper. Cecilia Berlin contributed to planning the focus groups, provided support during the data analysis, and reviewed the paper. Thorsten Wuest and Johan Stahre reviewed the paper and provided comments and advice.

Paper C. Jon Bokrantz designed the study and conducted the focus groups and interviews. Moreover, Jon performed data analysis, created the contingency model of Smart Maintenance, and wrote the paper. Anders Skoogh contributed to planning the focus groups and interviews, and reviewed the paper. Cecilia Berlin contributed to planning the focus groups, provided support during the data analysis, and reviewed the paper. Thorsten Wuest and Johan Stahre reviewed the paper and provided comments and advice.

Paper D. Jon Bokrantz designed the overall study and conducted each of the sequential steps of the research: generation of items, content validation and the empirical pilot. Furthermore, Jon performed data analysis and wrote the paper. Anders Skoogh, Cecilia Berlin and Johan Stahre reviewed the paper and provided comments and advice.

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APPENDICES

LIST OF ABBREVIATIONS

AI – Artificial Intelligence
ANOVA – Analysis of Variance
BCM – Business Centred Maintenance
CBM – Condition Based Maintenance
CFA – Confirmatory Factor Analysis
CFI – Comparative Fit Index
CMMS – Computerized Maintenance Management System
EFA – Exploratory Factor Analysis
ICT – Information and Communications Technology
IT – Information Technology
KSAO – Knowledge, Skills, Abilities and Other characteristics
MES – Manufacturing Execution System
ML – Machine Learning (in the context "data-driven decision-making")
ML – Maximum Likelihood (in the context "ML-based EFA")
OM – Operations Management
PA – Parallel Analysis
PHM – Prognostics and Health Management
PLM – Product Life Cycle Management
RBM – Risk Based Maintenance
RCM – Reliability Centred Maintenance
RMSEA – Root Mean Square Error of Approximation
SRMR – Standardized Root Mean Square Residual
TPM – Total Productive Maintenance
TQM – Total Quality Maintenance

I

INTRODUCTION

We live in a world of digital abundance. Digital technologies are everywhere, playing indispensable roles in everyday tasks such as transacting money, booking holidays, flying planes, driving cars, navigating traffic and recommending suitable music to play at parties. This is possible because digital technologies have become almost one million times better at computing, storing and communicating information in just three decades (Hilbert and López, 2011). Today, digital innovations can spread worldwide in an instant, at close to zero cost (Benzell and Brynjolfsson, 2019). It is therefore not surprising that information processing equipment and software has rapidly become the dominant category of business investments (Autor, 2014).

This rapid advancement of digital technologies applied to manufacturing is referred to as a fourth industrial revolution, and it is posited to dramatically transform the manufacturing industry. Digitalised production systems are envisioned to be intelligent, connected and responsive, in which machines and humans autonomously exchange information, trigger actions and control each other independently (Monostori et al., 2016). By now, the attention to all things digital in manufacturing can have eluded almost no one. Practitioners, policy-makers, researchers, governmental bodies and funding agencies all agree on the importance of digital. In fact, all the largest economies in the world have unanimously recognized that digital is the way forward. I collectively refer to this era as *digitalised manufacturing*, and to put it simply, this is where we are heading.

However, there is one major catch. The catch is that if all digital technologies would abruptly stop working, it would be like a full-frontal collision with a truck. Dead stop. For a manufacturing firm, this means zero products produced and zero profits. Therefore, in order to secure the success of digitalised production systems, industrial maintenance management needs to advance from being a low priority sustainer of the technical status quo, to becoming a leading enabler of high performance manufacturing in digitalised environments. In this thesis this advancement of maintenance is referred to as “Smart Maintenance”. The basic leitmotif is that Smart Maintenance is necessary to realize digitalised manufacturing. In other words, without Smart Maintenance - no digitalised manufacturing.

1.1 VISION

I envision a future in which the manufacturing industry continues to play a key role in a sustainable, prosperous society. In this future, I see high performance manufacturing in digitalised environments, in which successful realization is in part attributed to the adoption of Smart Maintenance. In other words, Smart Maintenance enables production systems that are economically, ecologically and socially sustainable. The utopia is failure-free production.

1.2 PURPOSE AND AIM

The purpose of this thesis is to ensure high performance manufacturing in digitalised environments by enabling the adoption of Smart Maintenance. In order to achieve this purpose, a holistic understanding of Smart Maintenance is needed. Therefore, the aim of this thesis is to describe future scenarios for maintenance in digitalised manufacturing, as well as to conceptualize and operationalize Smart Maintenance.

1.3 RESEARCH QUESTIONS

Following on from the purpose and aim, three research questions are formulated:

RQ1) What future scenarios are expected for maintenance in digitalised manufacturing?
RQ2) How can Smart Maintenance be conceptualized?
RQ3) How can Smart Maintenance be operationalized?

To make the research questions clearer to a broader audience, it is important to explain the meaning of *conceptualization* and *operationalization*. Their meaning can differ across social sciences and engineering, which encompass two important audiences for this thesis (see Section 1.5). Within the social sciences, conceptualization can be understood as the process of creating an abstract, simplified view of the world by specifying a set of concepts and their relationships; operationalization can be understood as the process of enabling empirical measurement of concepts that are not directly observable. Within engineering, conceptualization can be understood as the process of generating ideas for solutions to problems; operationalization can be understood as the process of finding ways of implementing solutions. In this thesis, conceptualization should be seen as the *invention of ideas*, and operationalization should be seen as the *measurement of ideas*.

1.4 DELIMITATIONS

The research in this thesis is focused on *maintenance* of *production systems*, with production systems defined as "the people, equipment and procedures that are organized for the combination of materials and processes that comprise a company's manufacturing operations" (Groover, 2007). The targeted population for survey sampling has therefore been the manufacturing industry according to the SE-SIC industry classification. Still, it is possible that the results are also applicable in other closely related domains, such as maintenance of products or infrastructure, which are potential avenues for future research.

1.5 TARGET AUDIENCE AND STRUCTURE OF THE THESIS

The target audience for this thesis is diverse; researchers, practitioners, policy makers - all with different backgrounds, knowledge bases, and experiences. In order to make the content of this thesis understandable to this diverse audience, it is particularly important to clarify some of the differences between engineering and the social sciences. Here, I purposefully oversimplify to make a point. Maintenance research is above all an engineering discipline. The engineering DNA is practical problem solving, always searching for solutions; viewing success as the degree to which solutions solve problems. Utility is everything. In contrast, the social science DNA is understanding how and why things work the way they do, always searching for empirics; viewing success as the degree of accuracy in predictions and explanations. Validity is everything (for an elaborated view on these differences, see Holweg et al. (2018)). Although engineers and social scientists operate within the same scientific discipline, we do not all talk the same language; we do not see the same things; we at times live in different worlds. My challenge is that I am right there in between. I have a foot in both camps - I am an engineer that thinks, acts and writes much like a social scientist. While it can be tough to hit an engineering nail with a social science hammer, I find it both important and exciting. After all, science is a social process in which we learn by sharing beliefs. We are all in this together.

Therefore, I ask all the readers of this thesis a favour: if you identify primarily as an engineer, try to learn from the empirics of the social sciences. If you identify as a social scientist, try to learn from the practical problem solving of engineering. Furthermore, see this thesis as a guided tour through an open book, one from which you can pick and choose according to your preferences. The thesis (chapter 1-6) is targeted towards a practitioner audience with an engineering background, with an emphasis on presenting my research in an accessible way. In contrast, the four appended papers (paper A-D) are targeted to a scholarly audience. I also stress the fact that this thesis is written in such a way that it reflects my PhD journey. The three research questions were approached as a linear sequence where I progressed, learned and improved step by step. This means that by the end of this thesis, you will not find the typical synthesis that explains how a set of distinct findings add up to a final, unified whole. The fullest understanding of the research will be achieved by viewing it is as a learning process.

The thesis is structured as follows:

1 Introduces the background of the thesis and presents the vision, purpose, aim, research questions and delimitations.

2 Provides a frame of reference with respect to digitalisation in the manufacturing industry, maintenance management, operations management and psychometrics.

3 Explains and defends the research approach, including philosophy, research designs and research methods.

4 Presents the results from three empirical studies (I, II, III) in relation to the three research questions (RQ1, RQ2, RQ3).

5 Discusses the research results and provides answers to the three research questions, as well as discussing academic and practical contributions, and proposals for future work.

6 Summarizes the thesis and presents the final conclusions.

2

FRAME OF REFERENCE

This chapter provides the frame of reference that is relevant to the research presented in this thesis. A summary is provided for digitalisation in the manufacturing industry, maintenance management, operations management, and psychometric measurement.

In order to make this chapter accessible to the broad audience of this thesis, it is important to clarify the meaning of three critical elements of science that are usually referred to by means of certain scientific jargon. These three elements are *theory, concepts* and *constructs*. There is no consensus on a general definition of theory, and ironically, the definition of theory in practice is the complete opposite of the definition of theory in research. When we talk about "theory" in everyday terms, we usually refer to highly speculative claims that can be safely ignored. In contrast, when we talk about theory in research, we refer to the very foundation of scientific knowledge; theory is what we use to explain facts and make predictions (Holweg et al., 2018). A simple and inclusive definition of a scientific theory is "a statement of concepts and their relationships that shows how and/or why a phenomenon occurs" (Corley and Gioia, 2011). In other words, a theory should include a set of concepts that are clearly defined in specific terms, along with descriptions of the mechanisms that explain how and why the phenomena work the way they do (Roth, 2007). Evident from this definition, theories revolve around concepts, which is a term often used interchangeably with constructs. To avoid confusion, I prefer and advocate the following distinction (in line with e.g. Podsakoff et al. (2016)). Concepts are theoretical, they represent the ideas stemming from the process of conceptualization. Constructs are empirical, they represent the measurement of ideas stemming from the process of operationalization. In order words, constructs are proxies that imperfectly represent concepts in statistical models. Both are necessary for building and testing theory. Without constructs, it is hard to acquire knowledge about the behaviour of concepts. At the same time, without concepts, constructs represent nothing beyond the function formed by the data set (Rigdon, 2016).

This chapter presents the frame of reference in four sections (Section 2.1-2.4). The degree to which each section relates to the three research questions (RQ1-RQ3) is visualized in Figure 1. The figure acts as a tool for readers of this thesis to better understand how a variety of scientific literature across multiple disciplines relate to each research question. It also illustrates the development of my personal research interests and how that has come to shape me as a researcher (see Section 5.8 for further discussion).

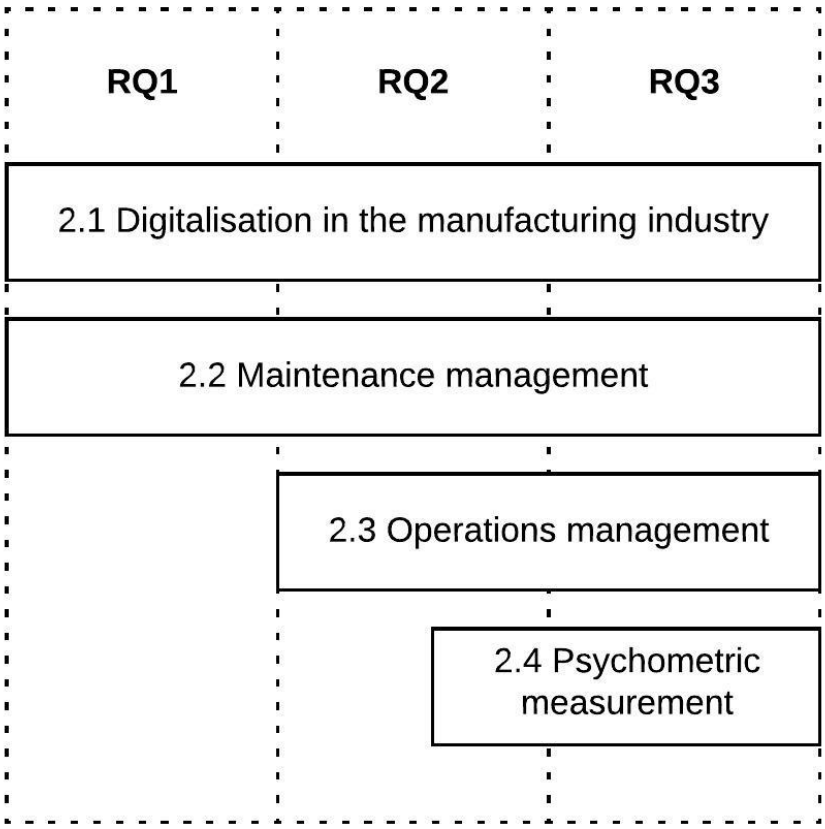

Figure 1. Research questions and related literature.

Firstly, *digitalisation in the manufacturing industry* (Section 2.1) puts all three research questions (RQ1-RQ3) into context by outlining current developments with respect to digitalisation. Secondly, *maintenance management* (Section 2.2) represents the core topic of this thesis, and thus relates to all three research questions (RQ1-RQ3). Thirdly, *operations management* (Section 2.3) constitutes a large source of theoretical and methodological inspiration for RQ2 and RQ3. In addition, it represents an important shift in my research approach, which was decisive for conceptualizing Smart Maintenance. Fourthly, psychometric measurement (Section 2.4) represents the measurement approach used for operationalizing Smart Maintenance in RQ3. This also played a significant role in defining and describing Smart Maintenance in RQ2 so as to enable it to be empirically measurable.

2.1 DIGITALISATION IN THE MANUFACTURING INDUSTRY

Maintenance of production systems is the core topic of this thesis. However, it is natural to begin by describing current developments within the manufacturing industry, so as to put this thesis into context. After all, "digitalised manufacturing" is explicitly stated in the sub-title of the thesis.

Digitalisation is currently affecting all parts of society and constitutes one of the primary research topics across disciplines. For example, economists are studying the impact of AI on labour, wages, employment and inequality (Autor, 2015; Brynjolfsson et al., 2017; Acemoglu and Restrepo, 2018a; Acemoglu and Restrepo, 2018b). Similarly, organizational scholars are untangling the implications of AI for organizational design (von Krogh, 2018; Raj and Seamans, 2019). Researchers within strategic management and information systems are focusing heavily on how digital platforms can be a source of competitive advantage (Yoo et al., 2012; McIntyre and Srinivasan, 2017; de Reuver et al., 2018). The impact of digital technologies on value chains constitutes a core topic within supply chain management (Waller and Fawcett, 2013; Ben-Daya et al., 2017; Tjahjono et al., 2017). In other words, digital technologies are posited to dramatically transform many parts of society, including the manufacturing industry (World Economic Forum, 2018).

Commonly spurred by the German initiative "Industrie 4.0" (Kagermann et al., 2013), governments, industrial firms and researchers are now working hard to realize a *fourth industrial revolution*. This has quickly become one of the most important topics in the realm of manufacturing (Liao et al., 2017). Manufacturing scholars are therefore focusing on a series of overlapping concepts, such as "Industry 4.0", "Smart Manufacturing" and "Smart Factories" (Hermann et al., 2016; Kang et al., 2016; Thoben et al., 2017). Achieving concept clarity with respect to these concepts is beyond the scope of this thesis, and I therefore collectively refer to this development as *digitalised manufacturing*. In essence, digitalised manufacturing entails the realization of production systems that are intelligent, connected and responsive, in which machines and humans autonomously exchange information, trigger actions and control each other independently. Such production systems are expected to be highly automated, remotely controllable in real-time and robust to deviations at every level, which in turn is expected to deliver substantial gains in productivity and resource efficiency (Monostori et al., 2016). The scope of this research stream has grown dramatically in recent years, and includes a variety of technical topics such as cyber-physical systems, internet of things, machine learning, cyber security and interoperability (Keepers et al., 2019; Mittal et al., 2019). Although research efforts are intense, especially in laboratory environments, industrial applications are still scarce. In addition, manufacturing firms are struggling with implementation issues such as large investment requirements, unclear benefits and lack of implementation guidelines (Liao et al., 2017). However, there is growing econometric evidence showing that manufacturing firms are indeed adopting more data-driven management practices, and that this makes them perform better (Brynjolfsson and McElheran, 2016; Brynjolfsson and McElheran, 2019). In sum, this thesis is specifically about maintenance of production systems in this new, digitalised manufacturing environment; hence its title: *Smart Maintenance – maintenance in digitalised manufacturing*.

2.2 MAINTENANCE MANAGEMENT

This section presents a short introduction to the overall topic of industrial maintenance management, an overview of historical and contemporary maintenance research, and describes different approaches used to conduct maintenance research.

2.2.1 *Maintenance management overview*

The most common definition of maintenance is "the combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform a required function" (CEN, 2001; EN 13306, 2010). This definition highlights the two basic categories of maintenance actions. *Preventive maintenance* is aimed at *retention* and is executed *before* a functional failure has occurred. *Reactive maintenance* (or corrective maintenance) is aimed at *restoration* and is executed *after* a functional failure has occurred (EN 13306, 2010). Moreover, according to this definition, maintenance actions can be applied to any item that performs a function. This thesis focusses on the maintenance of production systems, or *production maintenance*. In this context a production system can be defined as "the people, equipment and procedures that are organized for the combination of materials and processes that comprise a company's manufacturing operations" (Groover, 2007). In addition, "production systems include not only the groups of machines and workstations in the factory but also support procedures that make them work"(Groover, 2007). Therefore, production maintenance can most intuitively be understood as "procedures that make production systems work".

Maintenance is a critical support process that influences the well-being of a production system (Holweg et al., 2018). While conducted in the background, maintenance is deeply intertwined with the production process. For example, maintenance holds inventories (e.g. spare parts) that are necessary to ensure the functioning of production equipment. The delivery of maintenance actions is sensitive to the capacity of the process and queuing matters a lot (e.g. planning maintenance to avoid interruption of flow). The output of maintenance is a diverse set of tangible effects on process performance that cannot be inventoried but are consumed upon creation (e.g. availability). A narrow view on the main objective of the maintenance function is to maximize machine availability at minimum maintenance cost (Löfsten, 2000). However, this narrow view is limited on both sides: availability is not the only benefit of maintenance, and direct maintenance costs are not the only economic dimension of maintenance. Instead, the benefit of maintenance is better viewed in terms of the factors that influence availability - reliability, maintainability and maintenance support - as well as a range of other benefits such as improved quality (Muchiri et al., 2011) and reduced system-level idle times (Li et al., 2009). Maintenance economics is better viewed in terms of direct costs such as spare parts and labour, indirect costs such as defects and overtime due to breakdowns, as well as non-realized revenue such as missed deliveries and loss of sales (Ahlmann, 2002). Therefore, a holistic view of the objective of the maintenance function is to act as a comprehensive plant function that supports the production process by ensuring the functioning of the production system.

In order to improve industry practice, a plethora of maintenance concepts have been developed. These include but are not limited to Total Productive Maintenance (TPM) (Nakajima, 1988), Reliability Centred Maintenance (RCM) (Smith and Hinchcliffe, 2003), Condition-Based Maintenance (CBM) (Prajapati et al., 2012), Total Quality Maintenance (TQM) (Al-Najjar, 1996), Business-Centred Maintenance (BCM) (Kelly, 1997) and Risk-Based Maintenance (RBM) (Jones, 1995). The overall purpose of these maintenance concepts is to facilitate planning, control and improvement of maintenance actions; in other words, *maintenance management*. Over time, maintenance has evolved from a low status necessary condition (Pintelon and Parodi-Herz, 2008) – one that you must have but constantly need to debate and decrease the budget for (Salonen and Deleryd, 2011) – towards a strategic, integrated and holistic plant function (Pintelon and Parodi-Herz, 2008).

A special interest among maintenance scholars and practitioners has been the use of computers, as well as other Information and Communications Technology (ICT), to improve maintenance practices (Pintelon and Parodi-Herz, 2008). Here, two main areas are emphasized: (1) optimization of maintenance work and (2) organizational integration of maintenance. Since ICT increases the ability to process larger volumes and more diverse types of data, it is possible to achieve more advanced maintenance decision-making and closer collaboration with internal and external parties (Sherwin, 2000; Muller et al., 2008; Cannata et al., 2010). Much of this work is related to the concept of "E-maintenance", which does not have a consensus definition, but generally includes an array of technical, strategic and organizational aspects of maintenance management (Aboelmaged, 2015). With respect to technology, ICT has been seen as a key enabler for better decision-making and integration (Liyanage and Kumar, 2003), such as predicting the health status of equipment (Lee et al., 2006) and efficiently exchanging information with both internal stakeholders and suppliers (Candell et al., 2009). The maintenance field has developed considerably over the past two decades, especially with respect to decision-making models and CBM, where a wide range of data-driven, model-based and hybrid approaches have been developed. In addition, much work has been devoted to further improving the integration of maintenance with other organizational functions, such as production (Ruschel et al., 2017).

At present, the major scholarly focus is on maintenance in digitalised manufacturing. Although a variety of terms are used, such as "Prognostics and Health Management" (PHM), "Predictive Maintenance", "Maintenance 4.0" and "Smart Maintenance", the vast majority of research efforts are concentrated on improving maintenance decision-making (see Table 1 in appended paper B for a more detailed comparison). Contemporary topics include but are not limited to integrated maintenance planning, machine health assessment, big data analytics, degradation mechanisms, information system integration, optimization, self-healing, remote services, augmented and virtual reality, monitoring, diagnostics and prognostics (Lee et al., 2015; Roy et al., 2016; Vogl et al., 2016; Macchi et al., 2017; Ruschel et al., 2017; Kumar and Galar, 2018). There is also an emphasis on resolving technical constraints, such as data quality, infrastructure and security for data transfer, communication standards, and retrofitting of advanced sensors in legacy systems (Helu and Weiss, 2016; Vogl et al., 2016).

While academic research efforts on technology development are intensive, considerably less emphasis is put on soft issues. For example, it is acknowledged that in order to make use of modern technology, maintenance employees will need new and higher levels of competence (Dworschak and Zaiser, 2014; Weiss et al., 2016; Jasiulewicz-Kaczmarek et al., 2017). This requires not only large-scale investments in both professional and academic education, but also more careful attention to the alignment of technical solutions to the pre-requisites of maintenance professionals (Vogl et al., 2016; Weiss et al., 2016). Akkermans et al. (2016) provide a comprehensive, holistic and practically grounded view on maintenance in digitalised manufacturing. Specifically, it is argued that data-driven approaches to maintenance must consider a range of technological innovations (e.g. development of sensors, integrated IT systems and algorithms), cultural transitions and knowledge management (e.g. changing mind-sets, leadership structures and decision-making practices) and closer collaboration with other organizations (e.g. internally with top management and externally with suppliers and networks). This research stream was used as important input to developing the 34 projections in Study I (paper A), as well as in the theoretical background in Study II (paper B&C).

2.2.2 *Maintenance as a research field*

The academic discipline of maintenance consists of a multitude of topics, a variety of research methods, and a diverse set of perspectives on the world. However, a *discipline* is in part defined by its degree of coherence in a set of concepts, skills development, world views and particular lenses to problem solving. Like Operations Management (OM) at large (see Section 2.3.2), the maintenance discipline predominantly combines two main views on research: the engineering view and the social science view (Holweg et al., 2018).

Maintenance is above all an engineering discipline, which is clearly reflected in maintenance research. Firstly, the field holds an engineering view on concepts. In most cases, thinking about "maintenance concepts" implies TPM, RCM and CBM. More precisely, a maintenance concept is viewed as an optimized maintenance program that is created for each installation, for the purpose of planning, controlling and improving the maintenance actions and policies applied to the installation (Pintelon and Parodi-Herz, 2008). Simplified, a maintenance concept is a preventive maintenance schedule plus a repair policy (Sherwin, 2000). Maintenance concepts are also referred to as philosophies, approaches, models, methods, tools or techniques (Pintelon and Parodi-Herz, 2008).

Secondly, the dominant research mode is technology development. Owing to the field's origins within Operations Research, the development of maintenance decision-support, especially optimization models, has been a core activity of the field (Sherwin, 2000). This is motivated by the need to e.g. predict failure behaviour of equipment and optimization of maintenance planning (Pintelon and Parodi-Herz, 2008). However, the usefulness of this research stream has been criticized (Dekker, 1996; Zio, 2009; Sharma et al., 2011), in part due to the emphasis on mathematical precision at the expense of applicability, accessibility and connection to real-world practical problems (Sherwin, 2000). To this day, technological challenges persist as the main interest of the field (Helu and Weiss, 2016; Roy et al., 2016; Ruschel et al., 2017), with less emphasis on the social aspects that need to be addressed in order to secure its successful implementation (Akkermans et al., 2016). The historical emphasis on mathematically-oriented research is argued to be one of the main causes of the academic-practitioners gap within maintenance (Pintelon and Parodi-Herz, 2008). There is indeed much evidence that what is being developed in research is not reflected in industry practice. For example, industrial maintenance organizations are still largely reactive (Chinese and Ghirardo, 2010; Jin et al., 2016; Ylipää et al., 2017); often lack a formal strategy (Jonsson, 1997; Cholasuke et al., 2004; Alsyouf, 2009); and make little use of maintenance concepts such as TPM, RCM and CBM (Alsyouf, 2009) or rather basic Information Technology (IT)-solutions such as Computerized Maintenance Management Systems (CMMS) (Chinese and Ghirardo, 2010; Kans, 2013). A strong focus on real-world problems that are of interest to practitioners has been a key driving force that transcends the research presented in this thesis (Study I-III, paper A-D).

In contrast, the social science view on maintenance has called for two main perspectives: holism and empirics. Firstly, there have been many calls to view maintenance as a holistic phenomenon. This view takes into consideration all functions that are affected by maintenance, as well as the interplay between all organizational, human and technical elements. Less emphasis is put on micro topics, such as components and sensors, and there is more emphasis on macro topics, such as strategy, integration and supply chains. For example, Coetzee (1999) views the maintenance organization as an organism of which the parts function in full harmony towards the overall goals of the business. A holistic approach considers all the critical parts of the organization at the same time, including not just technology but also organizational climate, cross-functional collaboration, training and education of the work force. Tsang (2002) specifies four strategic dimension of maintenance management (service-delivery options, organizational design, maintenance methodology and support systems). Moreover, human factors and information flow permeate all dimensions, and emphasis is put on understanding organizational behaviour and conditions that stimulate people's minds and commitment. Jonsson (2000) describes maintenance in terms of three dimensions (prevention, hard integration and soft integration) that can be configured into various taxonomies for different operating contexts. Bengtsson and Salonen (2009) view maintenance from the perspective of systems theory, and argue that the development of strategies, skills, organization and culture is equally as important as new technology.

Secondly, this view has called for empirical research. For example, Swanson (1997) argues that although maintenance literature provides important conceptual models that add to the understanding of the maintenance function, these need to be empirically tested. In response to the lack of empirical evidence of CBM in real industrial settings, Veldman et al. (2011) show that assumptions about the design and implementation of CBM solutions do not hold against empirical evidence. Fraser et al. (2015) show that the amount of empirical research in maintenance is scarce, and call for much greater effort to produce research outcomes that are linked to real world problems. Because of the limited empirical tradition, the maintenance field has not focused extensively on construct measurement and empirical theory testing. Therefore, despite decades of research, there is a dire need for more understanding about how, and how well, the maintenance function is actually managed in industry. The social science view on maintenance is reflected throughout this compiled thesis, as well the specific results from each of the three studies (Study I-III, paper A-D)

2.3 OPERATIONS MANAGEMENT

The location of the maintenance function within the overall plant organization is analogous to the research field of maintenance management, being a subset of OM. Therefore, this section provides a short overview of topics and perspectives within OM that are relevant to the research presented in this thesis, as well as acting as sources of inspiration.

2.3.1 *Operations management overview*

Above all, the discipline of OM is about the design, measurement and improvement of *processes* (Holweg et al., 2018). A process can be understood as a sequence of activities that transform inputs to outputs. Most importantly for this thesis, a *production process* consists of a variety of inputs (e.g. material, components, labour, information, energy) that are transformed in a variety of conversion steps (e.g. by different production technologies) to become a variety of outputs (e.g. goods to be used as input in another process or consumed by end customers). *Management* is about "running the process" – planning, controlling and improving processes over time. Management involves a myriad of decisions, and the way *Operations* are *Managed* determines the output of the process (Holweg et al., 2018). Manufacturing firms thrive when processes are managed well, but firms struggle to survive when processes are managed poorly. Well-managed manufacturing firms have greater productivity, profitability, growth, survival rates and innovation (Bloom et al., 2019).

OM, at least in Europe, views production systems as socio-technical systems that consist of both hard systems (e.g. machines, equipment, information systems) as well as soft systems (e.g. people and social interactions). Both jointly determine the performance of a process (Holweg et al., 2018). Moreover, a system's view implies that there are several relationships that span across system (functional) boundaries. No function within a manufacturing plant operates in isolation, and viewing a single function as a self-contained field misses the fact that all functions have to operate in conjunction with each other (Holweg et al., 2018). Internally, OM research has primarily focused on the relationships between the primary plant functions, such as production, marketing, engineering and finance. Externally, focus has been on relationships with supply chains (Koufteros et al., 2005; Swink et al., 2007; Flynn et al., 2010; Schoenherr and Swink, 2012; Turkulainen and Ketokivi, 2012; Castañer and Ketokivi, 2018). These internal and external relationships serve to enable multiple types of flows: e.g. of material, data, information, knowledge, products, services, technology and money (Barki and Pinsonneault, 2005). The socio-technical view was an important part of the conceptual framing in Study I (paper A), and the holistic system view on internal and external relationships influenced the conceptualization of Smart Maintenance (Study II, paper B&C).

One essential topic within OM is *fit* (Sousa and Voss, 2008). Fit is rooted in contingency theory (Donaldson, 2001), which is a foundational logic within organizational and management science more broadly (Van de Ven et al., 2013). The basic rationale is that rules, policies, designs, technologies, people, structures etc. - let us jointly call them *elements* - are chosen so as to fit best in certain environments. Fit is rewarded with performance improvement (Donaldson, 2001), meaning that a central goal for managers is to achieve fit. It sounds easy, but the challenge is immense. Fit is a function of multiple elements and multiple environments, which can be both compatible and conflicting with each other depending on the context (Sousa and Voss, 2008). Moreover, most contemporary organizations are too complex and unpredictable to fully understand. This means that seldom, if ever, can a single set of elements be matched perfectly to a specific environment. Organizational links nowadays also transcend the internal functional boundaries of a manufacturing plant, and even functions located within an overall organization must expand and interact with external parties (Van de Ven et al., 2013).

Fit comes in two forms: external fit and internal fit. External fit is achieved by *alignment* of elements to environments, and internal fit is achieved by *configuration* of sets of mutually supportive elements (Sousa and Voss, 2008). Both external and internal fit is important at the same time (Miller, 1992). External fit is typically assessed with respect to the business environment and the institutional environment. Internal fit is typically assessed with respect to two forms of configurations: theoretically deduced *typologies*, and empirically induced *taxonomies*. Typologies are theoretically ideal configurations, and taxonomies are empirically observed configurations (Van de Ven et al., 2013). Therefore, fit must be viewed from a holistic perspective using a combination of good theorizing and empirical evidence (Van de Ven et al., 2013). Fit is the foundational logic for Study II (paper B&C).

2.3.2 *Operations management as a research field*

The engineering view and the social science view are both prevalent within the OM discipline. Rooted in Operations Research, the engineering side of OM is analytical with a focus on problem solving (Holweg et al., 2018). This research stream has historically dominated OM (Chase, 1980; Wacker, 1998) and produced many important insights on operational processes such as system dynamics (Sterman, 2000), stochastic modelling and queuing theory (Buzacott and Shanthikumar, 1993), the learning curve (Yelle, 1979), and factory physics (Hopp and

Spearman, 2011). Engineering OM uses a variety of methods from mathematics, statistics, computer science and simulation. With respect to methodology, engineering OM is highly concerned about the methodology used to solve specific problems (e.g. mathematical precision and statistics theory) (Bertrand and Fransoo, 2002).

Over time, this research stream has tended to lose its empirical foundation and was criticized for a lack of practical focus (Bertrand and Fransoo, 2002). Therefore, in the 1980s, calls by leading researchers were made to increase the attention to empirical research within OM as a means of narrowing the academic-practitioner gap (Buffa, 1980; Ackoff, 1987). Following a series of seminal articles (Meredith et al., 1989; Flynn et al., 1990; Swamidass, 1991), scholarly OM empirical inquires gained major traction and started to appear in mainstream OM journals (Gupta et al., 2006). Today, empirical research is the dominant research mode within the social science side of OM (Singhal et al., 2008). In fact, some authors hold the position that OM *is* a social science that requires more than practical problem solving, and that OM phenomena cannot be captured and explained in its entirety without empirics (Boyer and Swink, 2008). Therefore, empirical OM research focuses on the study of business processes with the development of theories that explain them (Holweg et al., 2018). With respect to content over time, empirical OM has moved from narrow, tactical micro topics such as inventories and manufacturing processes to more strategic, integrated and macro-topics such as supply chains and research methodology (Pilkington and Meredith, 2009). The main empirical inquiry within OM is the search for drivers of performance. The general objective is to use empirics to understand what practices lead to superior performance (Holweg et al., 2018); In other words, to provide answers to the question: if a plant does X, will performance improve? (Ketokivi, 2016). Empirical OM uses a variety of research methods, such as surveys, experiments, case-, event- and archival studies (Melnyk et al., 2018). With respect to methodology, empirical OM is highly concerned about the research methodology used to build, elaborate and test theories (e.g. research design, data collection and construct validity) (Bertrand and Fransoo, 2002). The philosophy, as well as research designs and methods embedded within empirical OM, has acted as a big source of inspiration to the methodology used within of all three studies, especially Study II and III (Paper B-D).

Empirical OM does not have a single uniform theory, or even a set of coherently used theories. Rather, theories are often borrowed from other disciplines. More or less all empirical OM use theory to ground their findings to some degree (Holweg et al., 2018). Arguably the most common case is to borrow theory from adjacent fields, such as strategy, organization, and economics (Anand and Gray, 2017). Some examples are contingency theory (Donaldson, 2001), resource-based view (Barney, 1991), information-processing view (Galbraith, 1974), and transaction cost economics (Williamson, 1975). When done well, this type of cross-fertilization is very valuable and enriching. The convergence of perspectives from different management disciplines can be exploited to conduct more useful research in OM. However, there is a risk that borrowed theories do not work in the context and do not add anything to the interpretation. It is also hard to make a theoretical contribution to such theories by applying them in an OM context (MacCarthy et al., 2013; Holweg et al., 2018). Importing theory from other domains was a central aspect that influenced the design and execution of Study II (paper B&C).

2.4 PSYCHOMETRIC MEASUREMENT

Measurement can be viewed as the empirical assessment of a given, conceptual characteristic (Holweg et al., 2018). This section provides a short overview of psychometric measurement, which is the foundation for measurement in this thesis. In particular, it is the foundation on which Study III (paper D) was designed and conducted. "Psychometrics" is the field of psychological measurement, which is generally concerned about the measurement of e.g. skills, knowledge, abilities, personality traits and educational achievement (Borsboom, 2005). A large part of the field is devoted to development and validation of measurement instruments such as questionnaires and personality tests (Brown, 2006). Such instruments are usually referred to as "psychometric instruments", and they are widely used across the behavioural and social sciences (MacKenzie et al., 2011).

2.4.1 *Latent variable models*

A key part of psychometrics is the separation of *observed variables* from *latent variables*. Some variables are observable and directly measurable, such as speed, distance or temperature. However, many variables are unobservable and can only be measured indirectly, such as personality traits and beliefs. Therefore, *latent variable models* are used to measure and test how different latent variables are related to each other (Brown, 2006). A simplified illustration of latent variable models is provided in Figure 2. Concepts are represented by constructs in statistical models in the form of empirical, latent variables. The latent variables are in turn constructed from a set of observed variables, known as *indicators*. For example, the classic big five personality test uses a large number of questionnaire items that serve as indicators for five latent traits (openness, conscientiousness, extraversion, agreeableness, neuroticism) that together make up an individual's personality (Barrick and Mount, 1991). The overall goal is to minimize the validity gaps so as to achieve a model that behaves in accordance with what it intends to measure.

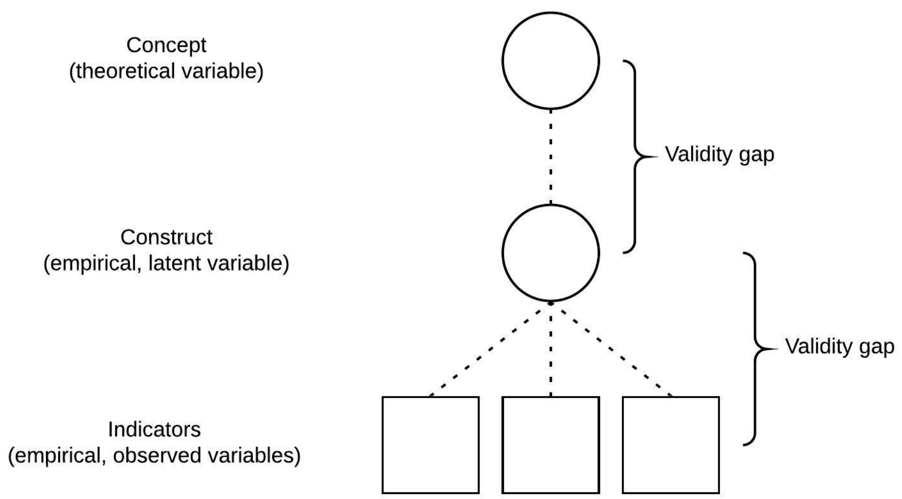

Figure 2. Illustration of latent variable models.

Latent variables can be measured in many different ways. One of the most extensively used statistical methods is *factor analysis*, which is the common term for a variety of statistical techniques for the resolution of a set of variables in terms of a smaller number of latent variables, called factors (Jöreskog, 1979). Factor analysis is used in many applied research fields, such as psychology, education, sociology, management, political science and public health. With respect to measurement instruments, factor analysis is used to examine the latent structure of an instrument. The purpose is to verify the dimensionality and the pattern of indicator-factor relationship by determining the number and nature of latent variables that account for the variation and covariation among a set of indicators (Brown, 2006). Factor analysis is conceptually rooted in the *common factor model* (Thurstone, 1947), as illustrated in Figure 3.

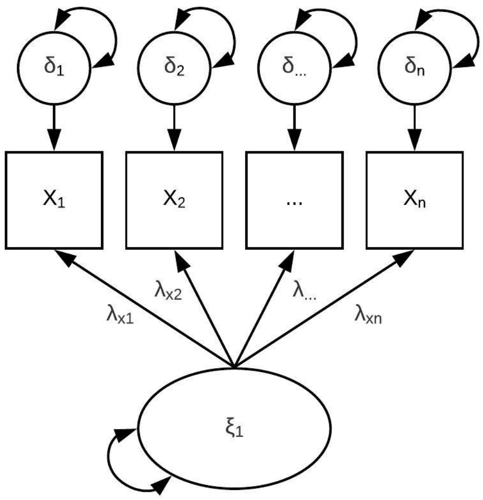

Figure 3. Common factor model.

A key feature of the common factor model is the consideration of measurement error. If only one indicator is used, it is assumed that the indicator is a perfect representation of the construct; that is, has zero measurement error. However, the common factor model acknowledges that each indicator is only an *imperfect reflection* of the construct; that is, each indicator has a non-zero measurement error that is explicitly modelled. By using a set of imperfect indicators, the collective measurement error of the construct can be reduced (Aguinis and Edwards, 2014).

When using factor analysis to estimate common factor models, each indicator (x) is specified as a linear function of one or more common factors (ξ) and one unique factor. Factor analysis separates the variance in each indicator into two parts: *common variance* and *unique variance*. The common variance is the variance in the indicator accounted for by the factor (λ), which is estimated on the basis of the shared variance with the other indicators in the analysis. The unique variance (δ) is the combination of variance that is specific to the indicator (i.e. variance that only influences one indicator) and random error variance (i.e. measurement error or unreliability of the indicator). The common factor influences more than one indicator and accounts for the correlation among a set of indicators. In other words, a set of indicators are correlated because they share a common cause. Factor analysis thus enables a more parsimonious understanding of the covariation between a set of indicators because the number of factors is smaller than the indicators (Brown, 2006). It is important to note that factor analysis according to the common factor model is often confused with Principal Component Analysis (PCA). Although factor analysis and PCA are similar with respect to the reduction of a set of observed variables into a smaller set of latent variables, they are conceptually distinct and have different aims. The most important difference is that factor analysis aims to account for the *covariances* among observed variables, while PCA aims to account for the *variances* of the observed variables (Jöreskog, 1979).

Applied use of factor analysis typically consists of first generating a set of questionnaire items, followed by examining the plausibility that a single factor or multiple factors account for the correlations among the items, as well as that all items are reasonable indicators for the underlying construct(s). There are two main types of factor analysis: Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) (Jöreskog, 1969). Both EFA and CFA are based on the common factor model and reproduce the relationships among a set of indicators with a smaller set of latent variables. However, they differ with respect to the a priori specifications and restrictions imposed on the model. In general, EFA is used without first specifying the number of factors and the expected pattern of relationships between the indicators and factors. Hence the term "Exploratory", which refers to it being a data-driven approach to find the appropriate number of factors and reasonable indicators. When using CFA, the researcher specifies the number of factors and the pattern of indicator-factor relationships in advance. Hence the term "Confirmatory", which refers to testing how well a pre-specified solution reproduces the correlation among the indicators (Brown, 2006). However, the development of factor analysis has made the wording Exploratory and Confirmatory somewhat misleading. Today, EFA can also produce standard errors that are used for hypothesis testing about the model, meaning that the main practical difference between EFA and CFA is the restriction of cross-loadings (freely correlated in EFA but restricted to zero in CFA) (Schmitt, 2011). The measurement instrument in Study III (paper D) was developed on the basis of the common factor model, specifically in the form of creating latent variables models by means of factor analysis.

2.4.2 *Construct measurement and validation*

Measurement instruments should be both reliable and valid; that is, consistent across time, individuals and situations with little measurement error (reliability), and should measure what it intends to measure (validity) (Ketokivi and Schroeder, 2004). There are multiple types of validity with respect to measurement instruments, such as content validity, discriminant validity, nomological validity and predictive validity (MacKenzie et al., 2011). When using factor analysis, reliability and validity are assessed on the basis of a number of statistical criteria. In general, two main hypotheses are evaluated: (1) does the model fit the data well? and (2) are the relationships between the indicators and the factors significant? (Brown, 2006). Model fit is evaluated using both exact and approximate fit statistics. For example, the chi-square test is a test of exact fit, i.e. that the sample covariance is equal to the model implied covariance. Approximate fit statistics include e.g. Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI) and Standardized Root Mean Square Residual (SRMR). These statistics provide additional information about model parsimony, the amount of departure from the researcher-specified and a null model, as well as the overall difference between the observed and predicted correlations. The relationship between the indicators and factors are evaluated using e.g. factor loadings, indicator reliability and factor determinacy (Brown, 2006; MacKenzie et al., 2011; Schmitt, 2011).

When measuring latent variables within OM, measurements known as perceptual measures are most common. The measurement instrument developed in Study III (paper D) is perceptual. The reason perceptual measures are extensively used within OM is because “objective” data rarely exists for the concepts of interests at higher levels (e.g. groups, functions, plants); some concepts are partly or completely “subjective” (e.g. customer satisfaction); and many studies seek statistical generalizability across industries or countries that are not producing the same type of product with the same type of production system under the same conditions (Ketokivi and Schroeder, 2004). For example, perceptual measures can consist of asking managers to respond with regard to the perceived uses of a certain practice, or their perceived financial performance relative to competition, on 1-5 scales. It is natural to initially react with scepticism against perceptual measures, questioning e.g. whether the informants are honest, answer about what is or what should be, or whether everyone interprets the questions similarly (Ketokivi and Schroeder, 2004). Perceptual measures are indeed subject to several biases that threaten validity, but they can be overcome (Melnyk et al., 2018).

In accordance to true score theory, the basic premise is that each measure has a true, objective score that differs from the observed, contaminated score. Contamination comes in the form of *systematic error* and *random error*. Systematic error affects several variables in a similar way, while random error affects single variables (Lord and Novick, 1968). The problem is that while researchers are interested in the true scores, it is the contaminated scores that are observed (Ketokivi and Schroeder, 2004). Although factor analysis aims to capture this contamination by isolating the unique variance, the disturbance term can be substantial. In survey research, there are two main types of bias: (1) common method bias and (2) respondent bias. Common method bias typically occurs when the same respondent provides ratings on multiple variables at the same time, and arises due to e.g. repetitiveness of the items, the response format and instructions. Respondent bias can arise from e.g. lack of knowledge and proficiency, different perceptions of the constructs of interest, and limitations in providing information about a broad range of practices that resides at the system level (Ketokivi and Schroeder, 2004; Melnyk et al., 2018). These biases can be reduced by means of both procedural remedies (e.g. using multiple respondents, careful survey design and enhancing respondent motivation) as well as post-hoc statistical remedies (e.g. multitrait-multimethod analysis) (MacKenzie and Podsakoff, 2012; Ketokivi, 2019). Perceptual measures are suitable for large-sample studies, and do meet the requirements for validity and reliability when the research is well designed and rigorous statistical examinations are performed (Ketokivi and Schroeder, 2004). Several strategies for reducing and/or eliminating common method bias and respondent bias were used throughout Study III (Paper D).

3

RESEARCH APPROACH

This chapter provides an explanation of the research approach, including perspectives on philosophy, an overview of the deployed multiple methods research approach, and a summary of research design and methods used in the three empirical studies.

A research approach consists of three interconnected elements: philosophy, research designs and research methods. The philosophy contains a set of ontological and epistemological beliefs that influence the choice of designs and methods (Creswell, 2013). Philosophy is the means by which researchers understand each other's preferences, and preferences must be acknowledged in order to understand how they influence choices (Gould, 1996). I hope that this chapter can serve as inspiration to my peers who are interested in pursuing empirical research, as well as to practitioners and policy-makers interested in the craftsmanship of science.

3.1 PHILOSOPHY

It is human nature to hold the greatest appreciation for things which we are most familiar and comfortable with (Boyer and Swink, 2008). Therefore, in this section, I disclose my personal preferences with respect to two components that I believe to be fundamental to the success of the scientific field of industrial maintenance management: *empirical research* and *multiple methods*. These components are fundamental because they can together overcome two overlapping and classic challenges of applied science: bridging the *academic-practitioner gap*, and resolving the *rigor-relevance debate*.

The overarching goal of empirical research is to inform policy and practice (Antonakis, 2017). By means of building, elaborating and testing theories about phenomena, empirical research can produce scientific knowledge that is capable of prescribing actions to issues that are of interest to policy-makers and practitioners. Empirical research typically begins with identifying phenomena that are important to practice, followed by clarifying them in the form of carefully defined concepts. Thereafter, plausible explanations for the phenomena are provided in the form of hypotheses for how and why the concepts are interrelated, followed by formally testing them against empirical results. By continuous refinement and modification; cycling back and forth between theory and empirics; it is possible to build and test theories that are important to industry (Fisher, 2007; Roth, 2007). Therefore, empirical research is fundamental if academics within the field of industrial maintenance management ought to be capable of bridging the academic-practitioner gap.

Moreover, this gap overlaps with the rigor-relevance debate (Antonakis, 2017). At the heart of the debate lies the idea that answers provided by rigorous research are often of little interest to practitioners (rigorous but not relevant). In contrast, practical prescriptions unsupported by thorough academic research, no matter how intriguing, might do more harm than good (relevant but not rigorous) (Vermeulen, 2005). However, in the view that I uphold of empirical research, there is no "debate" at all, it is a false dichotomy (Antonakis, 2017). Research is relevant when it is capable of informing policy and practice, and only research that is rigorous is capable of informing policy and practice. Rigor and relevance are intertwined. They co-exist. This co-existence is in fact the classic meaning of *usefulness* (Dewey, 1916 [1980]). Scientific knowledge is useful when it is capable of recommending successful actions, and this knowledge must be valid and reliable, otherwise it is not useful (Dewey, 1938 [1991]). Put in other words, useful empirical research is relevant because it asks the right questions, as well as rigorously applying the right methods to provide the answer.

In order to conduct useful empirical research, I am wholeheartedly convinced that *multiple methods* are needed. All real-world phenomena that are truly interesting to both researchers and practitioners are too complex to understand using a single lens. A single way of looking at the world will inevitably leave out some details. Therefore, multiple methods must be used in order to develop a realistic and holistic understanding of complex phenomena. The production of scientific knowledge includes both creating abstractions from reality and testing such abstractions against real world empirics, and this is simply impossible without the use of a diverse set of methods. There is neither one single best method, nor types of methods that are always superior to others, and multiple methods can be used alone or in combination (Boyer and Swink, 2008; Singhal et al., 2008; Gehman et al., 2018). Multiple methods are a hallmark of the social sciences in order to achieve convergence and completeness of scientific knowledge (Campbell and Fiske, 1959). This can even be traced all the way back to Aristotle in the form of the age-old idea that wisdom is produced through a multiplicity of lenses (Page, 2018). It is actually even simpler: multiple methods perform better. It is like a diversified portfolio of financial holdings: the collection is more likely to yield highly productive output with lower risk (Boyer and Swink, 2008). In fact, any collection of diverse methods is more accurate than its average member. It is not even necessarily so that the most accurate collection of methods is the one with the best performing individual. Rather, each method can make up for gaps in the others, so that the collective error can be reduced to almost zero. With enough methods, we almost never make a mistake. This is known as the "wisdom of the crowds", or, in the words of Aristotle: using multiple methods will make you wise (Page, 2018).

3.2 AN EMPIRICAL, MULTI-METHODS RESEARCH APPROACH

This thesis provides answers to three research questions about future scenarios for maintenance (RQ1), conceptualization of Smart Maintenance (RQ2) and operationalization of Smart Maintenance (RQ3). The three research questions were approached as a sequence. A total of three empirical studies were carried out to answer the research questions (Studies I, II and III), yielding a total of four publications (Papers A-D) (see Figure 4).

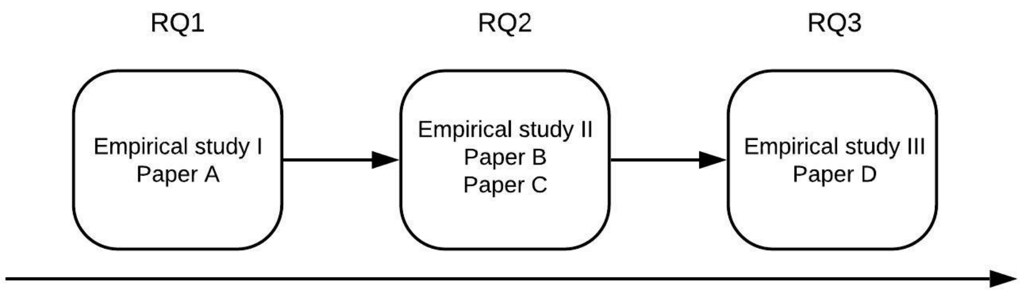

Figure 4. Overview of research questions (1-3), empirical studies (I-III) and appended papers (A-D).

An empirical, multiple methods research approach was deployed to provide answers to the three research questions. The approach combined both qualitative and quantitative research within and across the three studies. The general purpose of using both qualitative and quantitative methods is to achieve both breadth and depth of understanding; depth by means of words (qualitative) and breadth by means of numbers (quantitative) (Creswell, 2013). A key challenge for a multiple-method research approach is to achieve "question-method fit": where choice of method fits the objectives and context of the research. When fit is established, the most important thing is to design and conduct the research with rigor (Gehman et al., 2018). Therefore, to further clarify how and why multiple methods were used throughout the three studies, the sequential process in Figure 4 can be explained by means of a puzzle analogy (Kuhn, 1962). I hope that this description can provide a practitioner audience with a deeper understanding of the empirical research process. This understanding is important because if maintenance practitioners are interested in closely collaborating with researchers and contributing to the production of scientific knowledge, a certain degree of appreciation of theory and methodology is needed.

Phenomenon-driven research on maintenance in digitalised manufacturing

Digitalised manufacturing is often referred to as a (fourth industrial) revolution. However, it is not necessarily a revolution in a scientific sense; i.e. a complete shift in problems, standards and theories. Rather, the empirical research in this thesis is much like solving a puzzle. Scientific puzzle solving is about finding the pieces of the puzzle; making the pieces fit together; gradually covering all the holes. It is about articulating and clarifying ideas; categorizing ideas into boxes and connecting them with arrows; setting the standards for what constitutes legitimate scientific inquiry. Moreover, scientific puzzles always have solutions, which can be reached by following a set of rules, standards and acceptable steps (Kuhn, 1962).

The empirical, multiple-methods research approach deployed in this thesis contributes to solving the puzzle of Smart Maintenance. Smart Maintenance is analogous to the complete puzzle, and the research approach is analogous to the strategies used for solving the puzzle. The puzzle solving in this thesis has a particular characteristic; it is largely *phenomenon-driven*. Phenomenon-driven research aims to capture, describe, document and conceptualize new phenomena in the world (Von Krogh et al., 2012). It is typically characterized by formulating broad, open-ended research problems framed around the importance of the phenomenon (Eisenhardt and Graebner, 2007). Since there is no way of knowing how the puzzle will unfold from observations, the problem itself, as well as the solution, must unfold over time. In addition, multiple methods are often required in order to account for complex, ambiguous and often contradictory observations (Von Krogh et al., 2012).

RQ1 – future scenarios: study I and paper A

Study I provides answers to RQ1 in the form of future scenarios for maintenance in digitalised manufacturing. This study represents the initial stages of solving the puzzle. As any good puzzle-solver knows, the best strategy is to start by opening the puzzle box and spreading out all the pieces on a big table. In this way it is possible to get an initial overview of the size, scope and complexity of the puzzle. Based on the preferences and experiences of the puzzle-solver, different methods can then be used to find out whether some pieces are more important than others to start solving the puzzle. Some people prefer to start with all the corner pieces and assemble the complete frame. Others like to start in one corner and gradually build towards the middle. There might also be people who prefer to distinguish the seemingly random pieces from the most recognizable ones.

In Study I (see Section 3 in paper A), a qualitative phase was conducted first in order to develop 34 "projections" (short and concise future theses) about maintenance in digitalised manufacturing by the year 2030. The development of projections represented the process of creating a set of pieces for the puzzle and spreading them out on a table. This type of broad, exploratory work aimed at identifying problems is characteristic for the early stages of phenomenon-driven research, and it forms the foundation for more precise theory building (Von Krogh et al., 2012). Qualitative research is particularly suitable for identifying and verifying important phenomena on which one can do useful research (Gehman et al., 2018). In other words, qualitative research is good for "setting the stage" (Singhal et al., 2008), especially when addressing topics where little previous theory exists because it concerns new phenomena in the world (Edmondson and McManus, 2007). Thereafter, in order to find out whether some pieces seemed to be more important than others, a second stage was conducted that included both qualitative and quantitative methods. A quantitative evaluation was used to achieve a broad understanding of the 34 projections, and a qualitative evaluation was used to achieve in-depth understanding of eight probable scenarios and three wildcard scenarios. In other words, the approach used to answer RQ1 provided a set of pieces for the puzzle, as well as an initial structure in the form of finding some pieces that appeared to be more important than others.

RQ2 – conceptualization: study II and paper B & C

Study II (see Section 3 in paper B&C, as well as Appendix A&B in paper B) provides answers to RQ2 in the form of conceptualizing Smart Maintenance. This study represents the stages of starting to assemble the pieces into a more coherent and clear picture, so as to achieve a puzzle that you can begin to understand. Now, the puzzle solver starts to get to look at the harder sections of the puzzle. In order to progress, it is effective to zoom in on smaller sets of pieces that are similar to each other, gradually grouping them closer together. It is hard to work on the entire puzzle at once, so it is useful to ignore some pieces for a while and instead focus on the most important portions first and complete them step by step. Here, some pieces will represent the really distinguishing parts of the puzzle, like the centrepiece or the unique details of the background. These pieces are usually shaped a lot differently from the rest, so it is wise to keep them separate. Other pieces are easier because they simply do not fit together. To remain focused and structured, it is advisable to place the finished sections where they would be in the puzzle, even if there are still plenty of holes. It will take a lot of time to finish it all, but at this stage it is possible to clearly see the most important tendencies that will come to shape the complete puzzle.

Although Study I provided an initial structure of the puzzle, it was still too incoherent to be understood. That is, the projections and scenarios did not constitute clear, distinct concepts suitable to be operationalized (this is discussed in depth within the interim discussions in Sections 4.1.4 and Section 4.2.4). Therefore, Study II focused on making the puzzle clearer by moving from a broad set of projections and scenarios towards more precise theorizing. Consequently, a qualitative study was conducted in order to conceptualize Smart Maintenance. The general purpose of conceptualization is to organize, categorize and describe phenomena so as to provide researchers with a common language with which to communicate their ideas to each other (Podsakoff et al., 2016). Well-defined, distinct concepts are the essential building blocks of useful theories and therefore critical to high-quality empirical research (Gehman et al., 2018). Qualitative research is a key to good conceptualizations (Podsakoff et al., 2016), particularly because it allows for deep immersion in the phenomena of interest (Eisenhardt and Graebner, 2007) and understanding of real problems and issues in organizations (MacCarthy et al., 2013).

Moreover, conceptualization is a key component of phenomenon-driven research, and early engagement with practitioners is important to capture observations of not only focal concepts, but also antecedents and consequences (Von Krogh et al., 2012). By zooming in on the qualitative data, gradually grouping them together using a multiplicity of lenses, it was possible to reach a clear picture of the really distinguishing parts of the puzzle. These parts consisted of the defining dimensions of Smart Maintenance, the most important dimension of performance, and a diverse set of influencing contextual factors. Thereafter, by matching them together, these parts could be placed where they should be in the puzzle, thus forming a complete model of Smart Maintenance. This model shapes the path to understanding *how* and *how well* maintenance functions in manufacturing plants do things. In other words, the approach used to answer RQ2 provided clarity with respect to the important concepts and their relationships, and this is what will come to shape the puzzle of Smart Maintenance.

RQ3 – operationalization: study I and paper D

Study III (see Section 3 and 4 in paper D) provides answers to RQ3 in the form of operationalizing Smart Maintenance. This study represents the stage of starting to figure out whether the really distinguishing parts of the puzzle have been assembled correctly. This stage can be really tricky, because sometimes it will look like the pieces fit together like they should, but in the end, they will not. To be certain, the puzzle-solver needs to carefully check whether the pieces that have been grouped together really fit as a coherent whole, as well as to check whether the groups of similar pieces are really shaped differently from one another. If not, the puzzle solver might end up with the painstaking process of having to break the pieces apart and start all over again.

In Study III, a sequential, quantitative process was conducted to make parts of the puzzle observable so as to test whether the pieces fit together well; more precisely, to develop a psychometric measurement instrument that measures the degree of Smart Maintenance in manufacturing plants. Surveys and psychometric instruments are particularly useful for theory testing (MacCarthy et al., 2013). Theory testing research, in turn, relies on the quality of measures, and careful quantitative research is used to develop valid and reliable instruments that behave in a manner consistent with what it intends to measure (MacKenzie et al., 2011). The sequential process in Study III consisted of generating a large pool of items intended to capture the domain of the four dimensions of Smart Maintenance; assessing the adequacy of each item; collecting data from a set of manufacturing plants; and testing the factor structure that represents the instrument. Owing to this process, it was possible to check whether the four groups of pieces of the puzzle that represent the dimensions of Smart Maintenance fit together, as well as to confirm that they are shaped differently from one another. In other words, the approach used to answer RQ3 made Smart Maintenance observable, and this makes it possible to scientifically test whether the Smart Maintenance puzzle really looks the way it should.

Finalizing the Smart Maintenance puzzle

Building, elaborating, testing, refining and testing theories again is the cyclic process of empirical research that leads to recommendations of successful actions. I am confident that the field of industrial maintenance management can collectively work on solving the puzzle of Smart Maintenance for many years to come, not only because it takes years to solve a puzzle of this complexity and scale, but also because ideas are getting harder and harder to find (Bloom et al., 2017). Therefore, in the General Discussion section (Chapter 5), I outline my views on both the individual and the collective future work that are needed to proceed with the empirical research presented in this thesis, ultimately progressing towards producing useful scientific knowledge that solves the puzzle of Smart Maintenance.

3.3 RESEARCH DESIGNS AND RESEARCH METHODS

Study I, II and III were conducted by means of multiple research designs and research methods. The common denominators for all studies were collection, analysis and interpretation of empirical data. An overview of the research design and methods used within the three empirical studies follows. Detailed methodological descriptions are available in each of the respective appended papers.

Study I (see Section 3 in paper A) used Delphi-based scenario planning to develop and evaluate 34 projections. Scenario planning is useful for assessment of future developments, long-term planning and decision-making in uncertain situations (Varum and Melo, 2010), which is especially valuable when industry is about to experience significant change (Schoemaker, 1995). The Delphi-method aims to develop expert opinion consensus about future developments formulated as projections (van der Gracht and Darkow, 2010), and is often integrated in scenario planning to enhance the quality of the research (Nowack et al., 2011). The study can be divided into two parts: (1) development and (2) evaluation of projects. The first part consisted of literature reviews and empirical work in the form of focus groups and interviews, for which qualitative data was coded in order to develop the 34 projections. The evaluation consisted of a three-round Delphi-study in which web-based questionnaires were used to collect empirical data from a panel of maintenance experts. Quantitative data was collected in the form of estimations of probability, impact and desirability by means of Likert scales and percentages. Qualitative data was collected in the form of written arguments along with the quantitative data entries. The qualitative data was analysed using open coding, and the quantitative data was analysed using descriptive statistics and regression analysis.

Study II (see Section 3 in paper B&C, as well as Appendix A&B in paper B) used a step-by-step procedure for conceptualization, inspired by the process proposed by Podsakoff et al. (2016). Qualitative data was collected by means of focus groups and interviews. The data was analysed using hierarchical coding in Nvivo, aimed at building data structures as inspired by Gioia et al. (2013). A multitude of general theories from organizational theory, strategy, economics and sociology were used to code and interpret the data. The data structures were then used to develop definitions of Smart Maintenance, model the concept structure of Smart Maintenance, and specify a contingency model of Smart Maintenance.

Study III (see Section 3 and 4 in paper D) used a sequential quantitative procedure to develop a psychometric measurement instrument of Smart Maintenance. Measurement instruments are built incrementally in multiple steps, and the procedure includes collection and analysis of several independent sets of empirical data (MacKenzie et al., 2011). Study III can be divided into two parts: (1) development of measures and (2) scale evaluation and refinement. The first part consisted of generating a large pool of items that capture the four dimensions of Smart Maintenance, followed by assessing the content validity of each item by means of Analysis of Variance (ANOVA). The second part consisted of collecting data for a pilot-test, followed by evaluating the model fit and psychometric properties of the instrument. Empirical data was collected from a sample of manufacturing plants, and the factor structures were tested using Parallel Analysis (PA) and EFA.

A summary of the research designs and research methods is provided in Table 1. The table includes the overall research design of the study, the main methods used for data collection and analysis, and examples of validation techniques. Additional discussions regarding academic rigor (e.g. validation) are available in Section 5.6.

Table 1. Summary of research designs and research methods.

Research design	Data collection methods	Data analysis methods	Validation techniques
Study 1 – Future scenarios			
Delphi-based scenario planning	Focus groups Interviews Questionnaires	Grounded coding Descriptive statistics Logistic and linear regression	Face validation of projections Anonymity, iteration, controlled feedback, statistical group response Desirability bias analysis
Study II – Conceptualization of Smart Maintenance			
Step-by-step procedure for conceptualization	Focus groups Interviews	Hierarchical coding (data structures)	Peer debriefing Intercoder agreement Member checking
Study III – Operationalization of Smart Maintenance			
Survey	Questionnaires	Analysis of Variance Parallel Analysis Exploratory Factor Analysis	Concept-measure consistency Quantitative assessment of content validity and factor structure

This chapter has summarized the overall research approach of the thesis as well as the research designs and research methods used within the three empirical studies. Brief methodological summaries are also provided, together with the results of each individual study, in chapter 4. Readers interested in detailed methodological descriptions should refer to the methodology chapter in each of the respective appended papers.

4

RESULTS

This chapter presents the results related to the three research questions, stemming from three empirical studies that yielded a total of four publications (appended to this thesis).

4.1 RESULTS: FUTURE SCENARIOS FOR MAINTENANCE IN DIGITALISED MANUFACTURING

This section presents the results from study I that are related to RQ1.

4.1.1 *Introduction*

The advent of digitalised manufacturing has spurred very ambitious expectations for future production systems. For example, factories of the future are expected to be autonomous, robust, predicable, and controllable in real-time, which is in turn expected to lead to dramatic increases in productivity (Kang et al., 2016; Monostori et al., 2016; Thoben et al., 2017). In order to meet these expectations it is obvious that extraordinary maintenance management is needed. However, there is a lack of understanding of what the realization of digitalised manufacturing entails for maintenance organizations specifically. In particular, there is little relevant, actionable scholarly guidance that considers both hard (technological) and soft (social) dimensions. Therefore, the aim of this study is to describe the most probable scenarios for maintenance in digitalised manufacturing by the year 2030. In order to achieve a holistic understanding of the future role of maintenance, two questions guided the research:

How will the internal environment (equipment, plant, and company level) of maintenance organisations change by 2030?

How will the external environment (extra-company and environmental level) of maintenance organisations change by 2030

4.1.2 *Methodology*

Detailed methodological descriptions are provided in Section 3 in appended paper A. The two questions are answered by means of *Delphi-based scenario planning*, which is a scenario planning study that incorporates the Delphi-method. The purpose of scenario planning is to assess future developments so as to support long-term planning and decision-making in uncertain situations (Varum and Melo, 2010). The purpose of the Delphi-method is to systematically develop expert opinion consensus (van der Gracht and Darkow, 2010). Specifically, the study consisted of two parts: (1) development of projections and (2) evaluation of projections. The first part utilized literature reviews, focus groups and interviews to develop 34 "projections" (short and concise future theses) about maintenance in the year 2030. In order to support the overall, conceptual framing of the research, a holistic model was developed that located the 34 projections at different system levels (Figure 5). The model consists of two environments (internal, external) and five levels (equipment, plant, company, extra-company, environmental). A complete list of all projections and their location within the model is available in Table 3 in appended paper A.

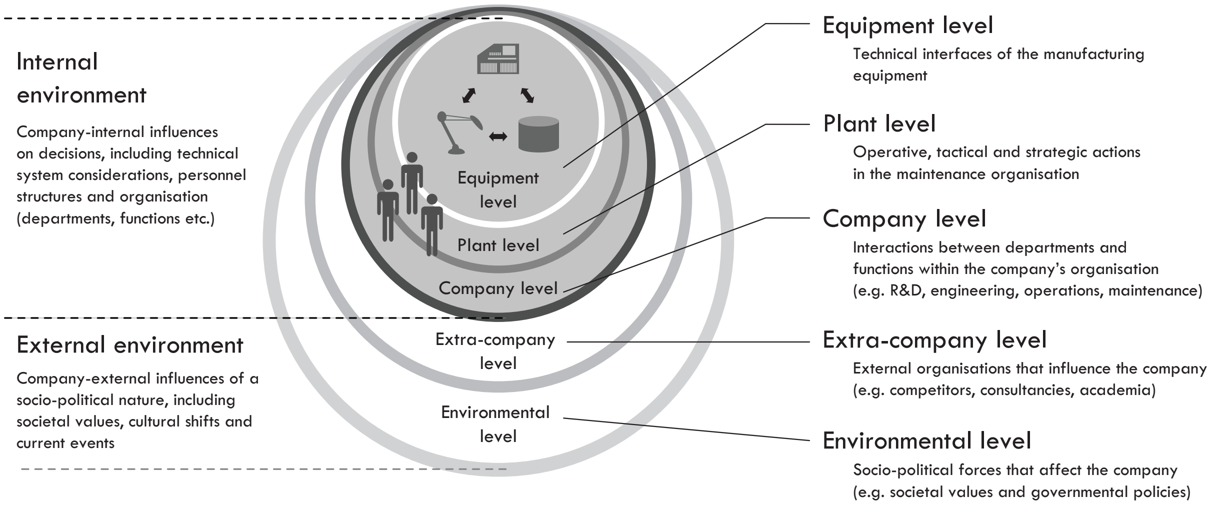

Figure 5. Holistic model with different system levels.

The second part recruited 25 industrial maintenance experts who evaluated the projections in a three-round Delphi study. In each round, the experts evaluated each projection in terms of estimated probability (EP), impact (I) and desirability (D), and also provided written arguments to support their estimates. The data was analysed using descriptive statistics and qualitative coding to identify and develop probable and wildcard scenarios. In addition, a series of regression analyses were used to evaluate desirability bias.

4.1.3 *Results*

Three types of results are provided: (1) quantitative results from Delphi projections, (2) desirability bias analysis, and (3) identification and development of scenarios. Firstly, the quantitative results from the three Delphi rounds are available in Table 4 in the appended paper. Two main observations can be made with respect to these results:

- All 34 projections are relevant to scholars and practitioners, as indicated by a median impact of 3 or higher in all projections (the majority having estimated probability of more than 50%).
- There is a convergence in the experts' opinion, which is the rationale of the iteration and controlled feedback of the Delphi method. All projections show a decrease in standard deviation, and consensus was achieved for a total of 30 projections.

Secondly, while the Delphi-method is capable of reducing desirability bias (experts assess desirable events as more probable, and undesirable events as less probable), it cannot completely eliminate it (Rowe and Wright, 1996). Therefore, a statistical post-hoc procedure was used to control for desirability bias, which provided insights that are complementary to traditional Delphi results. The procedure first identifies projections that are likely to carry the effect of desirability, followed by quantifying the consequences of desirability bias on the final results (Ecken et al., 2011). Two results illustrated over-optimism among the participating experts (see Table 5 in the appended paper):

- A total of 20 projections are significantly influenced by desirability bias
- All biased projections are over-estimated

Thirdly, two types of scenarios are identified from the impact-probability scatter plot in Figure 6. "Probable scenarios" are identified as projections with high probability (EP > 75%), high impact (I > 3) and consensus among the experts. "Wildcard scenarios" are identified as projections with low probability (EP < 50%) and high impact (I ≥ 3). A more detailed explanation of this logic is available in appended paper A. The data points in Figure 6 represent the 34 projections, with diamonds indicating consensus. The scenarios are thereafter developed based on the written arguments provided by the experts, in combination with literature review.

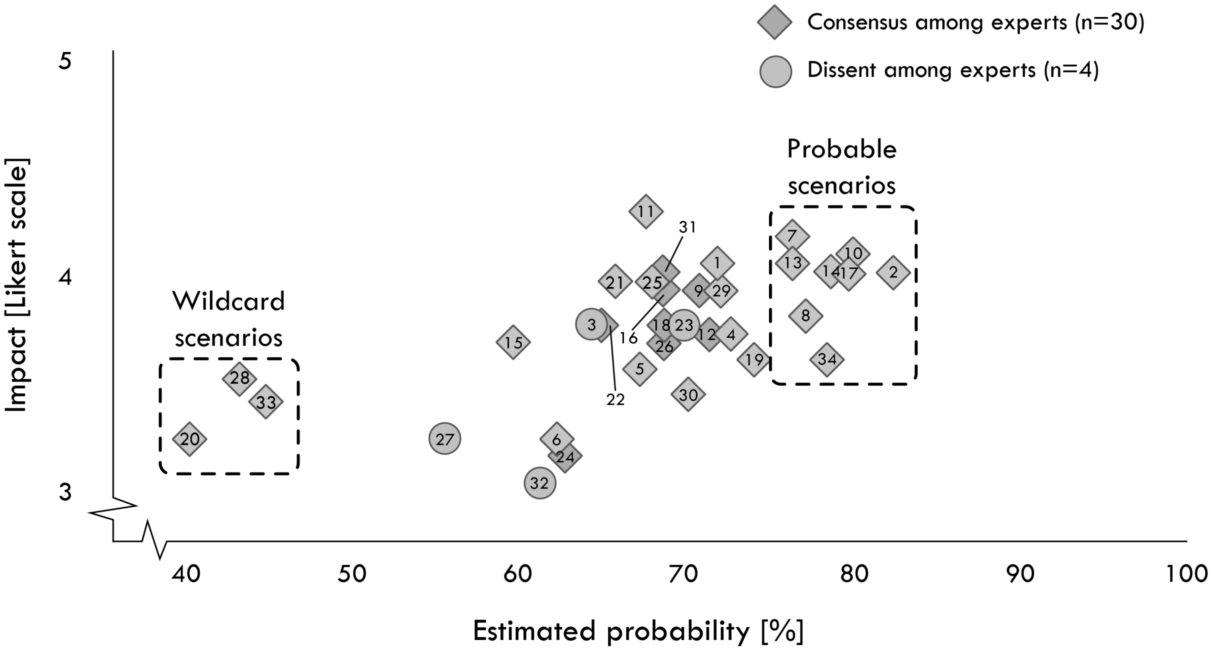

Figure 6. Impact-probability scatter plot.

A total of eight probable scenarios that are highly likely to influence the future of maintenance are presented in Table 2. The descriptions of each scenario include the most common arguments for high and low probability, along with a final conclusive narrative.

Table 2. Probable scenarios at different system levels.

No.	Probable scenarios at different system levels	
Equipment level		
2	**Data analytics**	
	Different types of data (e.g. physical, condition, events, context) from different sources and times are analysed together in order to detect patterns.	
	High probability Data collection (DC) is pervasive today, and the development of technology and software that supports data analytics will continue in the future. Data will be collected and analysed automatically in the future. Lower cost of DC and the development of data analytics and decision support accelerate this development. DC and analytics are an important way of working in complex processes and high-priority equipment. Data analytics from combined sources provide an overall picture of the manufacturing system and enable identification of patterns and root causes for equipment status and performance.	**Low probability** Difficult to motivate in the short-term. Too expensive to implement in simple equipment.
	Conclusion: Further developments of data analytics will enable maintenance organisations to effectively use data as decision support in 2030. The value of data analytics will lie in the ability to identify patterns and root causes and take proactive action to avoid disturbances and failures, thereby increasing productivity. This value will increase dramatically when several types of data are integrated, e.g. historical and real-time condition monitoring data, event data, and context data from the whole product population over time. The primary challenge will be economical justification.	
7	**Interoperability**	
	Standards for integration of information systems (e.g. CMMS, MES, PLM) have been developed and implemented in industry.	
	High probability Standards are a necessity to manage information in large manufacturing systems, e.g. collecting data from different equipment types, coordination and communication between all equipment in central systems, and managing different information systems from different equipment vendors. The work to develop standards has been initiated and implementation will therefore be reached by 2030.	**Low probability** The work with developing and implementing standards is too slow and will lag behind. Strong competition and a wide selection of information systems limit the possibility to agree on common standards.
	Conclusion: Standards will be necessary in order to reap the benefits of digitalised manufacturing since they enable interoperable information systems and thus horizontal and vertical integration. For maintenance organisations, interoperability standards enable integration of manufacturing equipment and information systems from different vendor platforms. Interoperability removes the constraint of adhering to proprietary platforms, thereby relaxing the need to buy unique equipment for specific demands. Challenges in reaching common standards by 2030 will include competition and unwillingness to abandon current proprietary systems.	
8	**Big data management**	
	Enormous amounts of data are generated from the equipment, and maintenance puts great emphasis on identifying and analysing the right data to make the right decisions.	
	High probability	**Low probability**

There will be enormous amounts of data, but the challenge lies in assuring competence, resources, and decision support systems to analyse it. The possibility to collect and analyse large amounts of data provides new possibilities to make better decisions in maintenance. Future decision support systems will automatically analyse data, making data analytics simple without the need for analysis personnel. A necessity for maintenance data analytics is to secure the data quality through a structured DC process, thereby only sorting and analysing relevant and correct data.	Due to limitations in time and human resources, a prerequisite is that maintenance systems automatically analyse data and present decision support.

Conclusion:
In 2030, manufacturing equipment will generate large amounts of data, which hold great potential as decision support in maintenance. However, data only has value when used, which requires the development of competence, resources and systems that enable maintenance organisations to make use of their data. Maintenance organisations will use data that adds value and enables decision-making, and will not waste time and resources on structuring, sorting and prioritising irrelevant data. Therefore, challenges will include achieving high quality maintenance data and developing maintenance management systems that automatically transform big data into decision support.

Plant level

10 **Education and training**

To secure necessary competence, maintenance puts great emphasis on continuous education and training of the workforce to keep up with technological developments.

High probability	**Low probability**
It is a necessity to manage future competence requirements and maintain competitiveness. New technology requires competence development. Education and training is prevalent today and will likely increase with new competence requirements. Changing competence profiles will require education and training.	It is uncertain whether top management realises the importance of education and training, or whether the organisation will dedicate the time required.

Conclusion:
In order to be competitive in 2030, continuous education and training will be an absolute necessity. The rapid development of digital technology demands that the competence profile of maintenance employees evolves at the same pace. Failure to develop a maintenance workforce that can effectively utilise the technology in future factories will increase sensitivity to disturbances, decrease responsiveness to failures, and reduce competitiveness. Challenges include communicating the need for education and training to top management as well as developing new innovative ways of training, e.g. skills assessment and monitoring, best practice experiences, and utilising ICT tools.

13 **Fact-based maintenance planning**

Fact-based decisions are the foundation for maintenance planning, particularly with the help of decision support based on predictive and prescriptive data analytics.

High probability	**Low probability**
A clear trend today that will increase in the future. Fact-based decision making is a key enabler for improving maintenance planning. A natural development alongside increased automation, interoperability of signals and systems, and improved data analysis methods. Will be an important complement to traditional maintenance practices.	Requires the development of better and more user-friendly tools, methods and systems for decision support.

Conclusion:
In 2030, maintenance organisations will have abandoned traditional ad-hoc planning and embraced fact-based planning. Predictive maintenance in 2030 predicts when disturbances and failures will occur. Supported with estimations of remaining useful life, maintenance organisations can base their planning on monitoring and prognostics rather than fault identification and diagnostics. Prescriptive maintenance in 2030 complements the prediction of disturbances and failures by also suggesting the most suitable counter-action. The economic impact will be substantial as fact-based planning increases availability, extends the life span of equipment, and enables more cost-effective maintenance with fewer

resources. The main challenge will be to incorporate predictive and prescriptive data analytics in user-friendly decision support systems.

14 **Smart work procedures**

New technology, data and analysis methods enables "smart work", e.g. real-time online monitoring and control, or remote inspection and repair.

High probability
The technology is already available today and will be increasingly utilised in the future with improved tools, methods and services.
Enables reduction of response times and repair lead-times and provides information to employees on-site.
There are no doubts regarding the technology, but the challenge lies in organisational aspects, collaboration with vendors, and standardised communication protocols.

Low probability
Inspection and repair will be performed on-site since they require physical actions.

Conclusion:
The adoption of digital technology is already advanced, and by 2030 these technologies will be utilised in smart maintenance organisations that are predominantly proactive. Real-time maintenance enables continuous monitoring of equipment performance and status, thereby enabling an overview of the manufacturing system and the ability to swiftly respond to disturbances and failures. Remote maintenance enables the provision of maintenance from anywhere, thereby reducing maintenance response times and repair lead-times. The challenge will not be building the technology, but rather getting people to use it properly and creating an organisation that fosters new ways of working.

17 **Maintenance planning with a systems perspective**

Maintenance is planned based on insights from individual machines (e.g. condition, alarms) combined with a systems perspective (e.g. bottleneck detection) with the aim of optimising the performance of the entire manufacturing system.

High probability
This approach is already prevalent today, but will be improved in the future through new technology and better decision support systems.
Enables maintenance to be planned with a flow perspective, where maintenance efforts are directed to achieve maximum effect on reliability and availability.
Focus on overall manufacturing system performance is a necessity for competitiveness.

Low probability
Appealing in theory but difficult in practice, especially in smaller companies.

Conclusion:
By 2030, maintenance planning will not be driven by the requirements of individual machines, but rather by the needs of the entire manufacturing system. Maintenance planning with a systems perspective aims at simultaneously maintaining multiple (similar or dissimilar) pieces of equipment in a manufacturing system so that maintenance efforts optimise the performance of the entire system. This planning principle can e.g. be manifested through differentiation and prioritisation of maintenance activities to the current manufacturing system constraint (i.e. bottleneck). The value of this principle will be the ability to maximise the effect from limited maintenance resources. The main challenge will be to develop and implement methods and algorithms in maintenance decision support systems that are useful in practice.

Environment level

34 **Environmental legislation and standards**

Stronger environmental legislation and standards (e.g. CO_2-emissions, energy consumption) have increased the pressure on maintenance, which is expected to ensure that equipment meets environmental requirements.

High probability
This trend is already prevalent - environmental requirements will increase and become more influential on maintenance in the future.
These requirements will increase for all organisational functions, including maintenance.
New technology will be useful in meeting environmental requirements, e.g. online monitoring and control of energy consumption.

Low probability
The environmental impact is primarily determined in the design phase.

Conclusion:

Maintenance organisations are already under pressure to meet environmental requirements today, but these requirements will continue to rise in importance by 2030. Since high equipment reliability is a necessity to comply with legislation and standards, maintenance will play a central role in achieving environmental sustainability. Promoting environmental sustainability in maintenance can also be of economic value as sustainable manufacturing companies may have a competitive advantage in 2030. Digital technology will aid maintenance organisations in meeting environmental requirements, e.g. through monitoring and prediction of energy consumption and failures causing high CO_2-emissions. The challenge will lie in raising the awareness of how maintenance contributes to sustainable manufacturing, e.g. improving resource efficiency, increasing life-length of equipment and reducing energy use, waste and emissions.

A total of three wildcard scenarios are developed, which are essential in scenario planning because they provide insights into future events that are less likely to occur, but that could have large impact on the industry (Grossmann, 2007). The wildcard scenarios are presented in Table 3 and include descriptions of promoting and hindering forces based on the experts' comments.

Table 3. Wildcard scenarios with promoting and hindering forces.

No.	Wildcard scenarios at different system levels	
Company level		
20	**The maintenance department has vanished and been replaced by a cross-functional organisation (maintenance, engineering, purchasing etc.) where teams deliver manufacturing as a service (e.g. OEE, uptime) throughout he manufacturing systems' life-cycle.**	
	Promoting forces Cross-functional teams with shared goals and common development resources can reach both broader and higher levels of competence.	**Hindering forces** Maintenance will need to remain as a separate department in order to ensure specific maintenance competence and resources and to prevent maintenance from becoming a function with unclear roles and responsibilities. The maintenance department will remain but will increase its cross-functional collaboration with other functions in order to broaden its competence profile. This type of organisational change requires large amounts of time and effort, since it challenges cultural barriers and conventional hierarchies.
Extra-company level		
28	**Various actors (e.g. manufacturers, machine vendors and service providers) share data and collaborate in digital networks on knowledge, competence, and new technology within maintenance.**	
	Promoting forces This type of collaboration could change the entire business strategy for some companies. With a changed world economic system, various actors could collaborate instead of solely competing for business.	**Hindering forces** This will be prevented by one factor above all else: competition. Data, information, knowledge, products, services and trade secrets are all regarded as competitive advantages and/or "hard currency" that will not be shared between companies. The risks of sharing data are too large: secrecy policies and difficulty in knowing who has access to the data slows this development. There is a difficulty in achieving obvious mutual benefits for all involved parties.
Environment level		
33	**Maintenance is visible in the social debate and influences e.g. legislation, policies, and the development of standards.**	
	Promoting forces The importance of maintenance in public infrastructure will be highlighted in the social debate; on the one hand its positive influence on profitability, safety etc., and on the other hand the cost of poor maintenance. The societal status of maintenance as a discipline determines its visibility in the social debate; factors that raise its status include increased research and clear organisation of maintenance issues. An increased understanding of the role of maintenance in achieving sustainability can improve the possibilities for maintenance to be visible in the social debate.	**Hindering forces** Other societal problems will dominate the social debate.

4.1.4 *Interim discussion*

The results from Study I provide 34 projections that are all relevant to scholars and practitioners; eight probable scenarios that describe the most probable future of maintenance organizations, as well as three wildcard scenarios that are less probable but could have large impact on maintenance in the future. In the discussion section of the appended paper, the results of the study are related to existing research within maintenance, as well as digitalised manufacturing more broadly.

In general, the results highlight the importance of upholding a holistic perspective on the future role of maintenance, which is manifested in several ways. Firstly, maintenance organizations in manufacturing firms will undoubtedly face both hard (technological) and soft (social) challenges, with both being keys to success. Using technology to create value requires not only the technology itself, but also the corresponding training and education of the workforce, as well as supporting work processes. Secondly, narrow theoretical solutions to complex practical problems are seldom useful, which highlights the importance for scholars to more carefully consider the needs, expectations and prerequisites of practitioners. Thirdly, optimism varies with time and place. The opportunities of digital technologies are hard to underestimate in the short-run, as manifested in sometimes exaggerated expectations. However, history has taught us that in the long-run, manufacturing companies tend to over-estimate the expectations for highly automated and complex production systems, but underestimate the importance of maintenance.

The results of the study contribute to cumulative research efforts with respect to maintenance in digitalised manufacturing. However, it is important to note that scenario planning is *not about predicting the future*. It is about describing plausible future events that question prevailing mind-sets and existing assumptions, so as to consider changes that might otherwise be ignored (Schoemaker, 1995; Ramirez et al., 2015). Scenarios are never ends in themselves – they are always input to something subsequent. For practitioners, it is input to long-term strategic development. For scholars, it is input to further understanding and more precise theorizing. Viewed with the design-thinking perspective of Nobel Laurate Herbert Simon (1996), applied researchers should be concerned with *creating desirable futures* – meaning that maintenance scholars can use the scenarios as guidance for actively shaping the path of industrial firms.

An intuitive research strategy could have been to conduct further work on the eight probable scenarios, e.g. by operationalizing each and every one of them and testing their relationships. However, I made a critical realization after Study I: in order to truly progress towards empirical measurement and theory testing, the key concepts embedded in the results needed to be clarified and defined, and their relationships specified. A lack of *concept clarity* increases the likelihood that operationalizations will be deficient and/or contaminated. That is, ambiguous and unprecise concepts are likely to contain greater levels of systematic and/or random error. Actually, one of the single main causes of measurement problems is a poor definition of the concept (Podsakoff et al., 2016). In particular, concepts need to be *both* conceptually and empirically distinct (Shaffer et al., 2016). Practically speaking, this means that one needs to both *argue* that the concepts are different from each other, as well as to *demonstrate* this empirically. One problem from Study I (also discussed in appended paper A) is with respect to the four projections *data analytics, big data management*, *fact-based maintenance planning*, and *maintenance planning with a system's perspective*. These projections can be argued to be conceptually distinct in the sense that they focus on different steps at different levels within the process of collecting, analysing and interpreting data for decision-making. However, empirical measurements of these projections are likely to show significant overlap and might not satisfy discriminant validity. Instead, one could argue that they are all reflections of the same underlying phenomenon, which could be meaningfully measured using a single latent variable.

Because of my long-term goal of achieving valid and reliable empirical measurements, I consequently stored the results and lessons learned from Study I in my bank of knowledge and experiences, pulled out a new blank sheet, and started again. In fact, gradually progressing towards more precise theorizing is characteristic for phenomenon-driven research (Von Krogh et al., 2012). This search for *concept clarity* takes us to Study II.

Table 4. Summary of results related to RQ1

- A total of 34 projections were developed from the literature, focus groups and interviews.
- A panel of 25 maintenance experts from large Swedish manufacturing firms was recruited.
- The projections were evaluated by means of a three-round Delphi study.
- Projections were classified as probable, impactful and desirable.
- Seven probable scenarios can be expected to influence the internal environment: data analytics, interoperable information systems, big data management, emphasis on education and training, fact-based maintenance planning, new smart work procedures, and maintenance planning with a systems perspective.
- One probable scenario can be expected to influence the external environment: stronger environmental legislation and standards.
- Three wildcard scenarios depict eventualities that are less probable but could have a large impact on maintenance in the future.
- Over-optimism about the future of maintenance was observed among the participating experts.

4.2 RESULTS: CONCEPTUALIZATION OF SMART MAINTENANCE

This section presents the results from study II that are related to RQ2.

4.2.1 *Introduction*

In response to the ongoing transition towards digitalised manufacturing, maintenance organizations are expected to exploit the opportunities of novel digital technologies. Therefore, most maintenance managers are interested in discovering how modernizing the maintenance function and operations impacts the performance of manufacturing plants. Locally in Sweden, this is referred to as "Smart Maintenance". However, decision makers and practicing managers struggle with defining and/or agreeing on what Smart Maintenance is, how it can be achieved, and what the benefits are.

Therefore, the aim of this study was to conceptualize Smart Maintenance. With this single, overall aim, Study II was deployed as a large-scale qualitative study. However, the volume of insights from the study resulted in two independent, yet topically connected papers (paper B and C). Paper B provides an empirically grounded definition of Smart Maintenance and its underlying dimensions, as well as a model of its concept structure. Paper C proposes an empirical research agenda for industrial maintenance management with respect to Smart Maintenance, containing a wide range of important context and performance variables as well as the overall pattern of their relationships. Together, the results provide a holistic understanding of Smart Maintenance, which are here presented in a single chapter.

4.2.2 *Methodology*

Detailed methodological descriptions are provided in Section 3 in appended papers B&C, as well as in Appendix A&B in paper B. The overall research design of the study was inspired by the step-by-step procedure for conceptualization (Identify; Organize; Develop; Refine) proposed by Podsakoff et al. (2016). Specifically, a series of 14 focus groups and 4 interviews were conducted with a total of 113 individuals, representing 22 different firms. The focus groups were centred around three questions aimed at uncovering the defining characteristics, consequences and opposite poles of Smart Maintenance (see the appended papers), whilst the interviews focused on illuminating specific emergent phenomena. The collected data consisted of 2410 written free-text answers (captured via the web-based platform "Mentimeter") and 179 pages of transcripts from the audio-recorded discussions and interviews.

The data analysis focused on building qualitative data structures by means of systematic coding of 1st and 2nd order codes, as well as aggregate dimensions (Gioia et al., 2013). The data structures are presented in the two appended papers, where the 1st order codes represent exemplar informant quotes, and the 2nd order categories and aggregate dimensions represent theoretical interpretations. Several rounds of peer-debriefing, member checking and intercoder agreement were used to increase the trustworthiness of the data and assess the reproducibility of the coding.

The data was analysed through a multiplicity of theoretical lenses. By integrating a set of general theories from organizational science, strategy, economics and sociology, it was possible to holistically interpret the qualitative data. Most importantly, the theoretical foundation of the study was *contingency theory* (Donaldson, 2001). Contingency theory is concerned with designing organizations so as to achieve internal and external fit. Internal fit is achieved by designing sets of mutually re-enforcing organizational elements (configurations), and external fit is achieved by aligning these elements to contextual factors (contingencies) (Van de Ven et al., 2013). Contingency research therefore focuses on fit amongst three types of variables: *context, response and performance* (Sousa and Voss, 2008). In the two appended papers, the empirical observations and theoretical interpretations are presented in a detailed and extensive manner for a scholarly audience. Therefore, in this section, the results are simplified and summarized for a practitioner audience.

4.2.3 *Results*

The findings with respect to the three types of variables are presented first, followed by illustration of their relationships in a contingency model. The context variables represent internal and external contingencies that explain adoption of Smart Maintenance; the response variables are the core dimensions of the Smart Maintenance concept, and performance is the outcome of achieved fit between contingencies and responses.

Smart Maintenance

Achieving clarity by defining, describing and modelling the Smart Maintenance concept is the central result of the study – it specifies *what Smart Maintenance is*. Figure 7 illustrates a simplified view the Smart Maintenance concept structure and its four dimensions (a more detailed illustration is provided in Figure 5 in appended paper B). This is followed by providing formal definitions and descriptions of the content within each dimension.

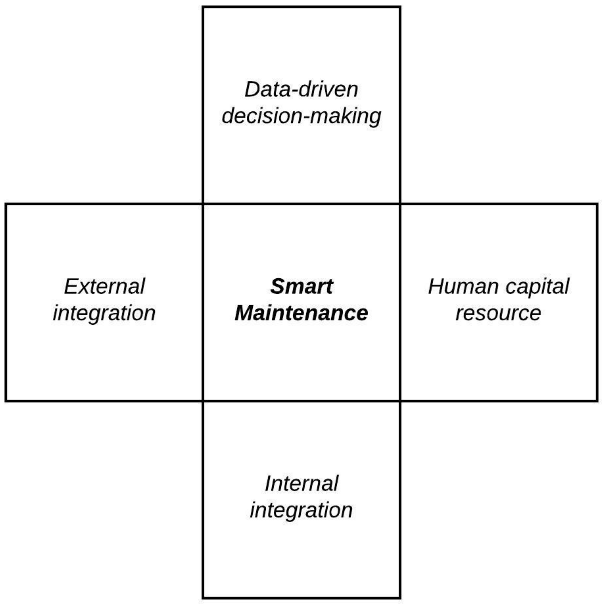

Figure 7. Smart Maintenance concept

Smart Maintenance is defined as 'an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies', consisting of its four underlying dimensions *data-driven decision-making, human capital resource, internal integration* and *external integration*. In other words, the four dimensions constitute what Smart Maintenance is. Moreover, the dimensions fit together because they support each other in symbiosis, and they are all necessary to achieve Smart Maintenance. For example, most maintenance managers eager to exploit the opportunities of digitalisation tend to see data-driven decision-making as the primary dimension to target in their strategic development. However, the structure of Smart Maintenance prescribes that in order to achieve data-driven decision-making, the plant must also achieve human capital resource, internal integration and external integration.

Data-driven decision-making is defined as 'the degree to which decisions are based on data'. In essence, the falling prices for technologies (e.g. sensors and computing power), in combination with rapid advancements of Machine Learning (ML), and Artificial Intelligence (AI) more broadly, have increased the capacity for maintenance functions to collect, analyse and interpret data to make better decisions. Better maintenance decisions on the basis of data can be achieved in two ways: decision automation, and decision augmentation. The first way refers to when technology substitutes human decision-making - e.g. predicting component failures and automatically planning the appropriate maintenance action. The second way refers to when technology complements human decision-making – e.g. combining the insights from data with the knowledge and experience of humans to classify and prioritize maintenance activities towards the critical equipment in the production system. The basic idea is that decisions based on data are more accurate than decisions solely based on experience or intuition.

Human capital resource is defined as a 'unit capacity based on individual knowledge, skills, abilities and other characteristics (KSAOs) that are accessible for unit-relevant performance'. Humans will remain an indispensable source of value creation within maintenance. Specifically, this dimension refers to the collective human capability that contributes to achieving the goals of the maintenance function. It is based on the human capital of the individual maintenance employees, but is also shaped by the interactions and relationships between them. The challenge is that technological change increases the need for both generic and specific KSAOs. For Smart Maintenance employees, this means both a higher requirement for generic skills, such as social, business, and technical skills, as well as a shift towards more specific types of analytical and ICT skills.

Internal integration is defined as 'the degree to which the maintenance function is a part of a unified, intra-organizational whole'. This has been a classic challenge throughout the history of time: the maintenance function must work more closely together with production and other functions within the plant. When the maintenance function is integrated with other functions, it facilitates the flow of data, information and knowledge across functional borders. Internal integration includes both people (e.g. cross-functional collaboration), processes (e.g. synchronizing maintenance and production planning), as well as technology (e.g. integrating the CMMS with other information systems).

External integration is defined as 'the degree to which the maintenance function is a part of a unified, inter-organizational whole'. Because of digitalisation, the maintenance function needs to access data, information and knowledge that resides outside the boundaries of the plant. In order to make use of the technological progress, innovation and accumulated knowledge that grows much faster outside the plant, maintenance functions must extend their organizational links to external parties, such as strategic partnerships with important suppliers or networks. External integration includes both people (e.g. communication with suppliers), processes (e.g. synchronizing buyer-suppler activities) and technology (e.g. integrating the plant's information systems with those of the suppliers).

Context

The context variables serve two purposes. Firstly, they influence the adoption of Smart Maintenance, that is, they provide explanations as to why plants choose to implement Smart Maintenance, and why implementation is difficult. Secondly, they influence the relationships between Smart Maintenance and performance, that is, they provide explanations as to why some plants receive more performance benefits than others.

Change context (leadership, corporate culture, algorithm interpretability)

Organizational change towards Smart Maintenance requires large amounts of managerial attention, time and effort to be successful. Three factors that can act as both inhibitors and facilitators to organizational change are *leadership, culture*, and *algorithm interpretability*. Leadership is decisive for successful organizational change of almost any kind and size, and more or less every change initiative will benefit from clear leadership vision and goals. Closely related to leadership is corporate culture, which can act as both a source of resistance to change and a catalyst to change. Changes that clash with the existing culture usually struggle to gain a foothold, but a supportive culture can create a virtuous cycle of change. While technical in nature, *algorithm interpretability* can be a source of initial, cultural friction that prevents current decision-making practices from being disrupted. Trust can be impeded in the form of anxiety about how advanced ML-algorithms influence the role of humans in the organizations.

Investment context (technology, complementarities, quantification of effects)

Implementing Smart Maintenance is not free. It will require a variety of financial investments. Most plants face the need to transition towards new technologies, and thereby invest in *Information- and Communication Technologies* (ICT), e.g. sensors, computing power, information systems and infrastructure to enable collection, storage and analysis of data. On one hand, this is eased by rapidly falling prices for digital technologies. On the other hand, enabling the effective use of digital technologies requires additional *investments in complementarities* that may be much larger. For example, training and education to acquire new skills, adapting work processes, or revising the relationships with internal and external parties. It is important to keep in mind that it is not technology itself, but the intangible assets enabled by technology, that create value. These are much harder to implement compared to simply investing in information systems. Finally, most maintenance managers would agree that getting approval for maintenance-related investments in not an easy task. Because much of the rationale behind maintenance investments is to avoid future consequences and costs of not performing maintenance, the economic value is rarely obvious to accountants. Therefore, being able to *quantify the effects of maintenance* in financial terms can support maintenance functions to motivate the entire range of investments in technology, skills and processes required to fully implement Smart Maintenance.

Interface context (digital platforms, openness, IT-security)

When a maintenance function extends its organizational links to span outside the plant, it faces a set of risks with respect to interacting with a large number of external parties. In particular, there is a growing market for trading the value that can be created from consolidated equipment data, but this type of digital business exchange gives rise to a set of risks that need to be managed. *Digital platforms* are perceived as one of the primary solutions for applying ML at scale, in the form of predicting and prescribing maintenance actions to a variety of plants by means of consolidated equipment data. Here, the platforms act as intermediaries that facilitate transactions in networks. To create this set-up in practice, substantial independent investments are required from both buyers and suppliers, so as to enable common, platform-mediated networks. When up and running, the value for each user depends on the number of other users in the networks (direct network effects), as well as the number of additional products and services offered through the network (indirect network effects). For example, multiple plants can connect all their equipment of the same or similar type to a common analytics platform provided by a single supplier. The consolidated equipment data are analysed in the platform, followed by returning individual recommendations to each plant. However, these effects will only occur if each party collaborates to the extent that the entire network can reap the benefits of scale.

There are two important factors that make the establishment of digital exchange relationships difficult: *Openness* and *IT-security*. These factors are sources of mistrust in digital exchange relationships, and trust is a necessary condition for economic transactions. Openness refers to the formal and informal rules for sharing, protecting and accessing that which is being shared by each party. Most actors in partnerships or networks are interested in receiving a value that is at least proportionate to what is being shared, but this is seldom a one-to-one ratio. With respect to consolidated equipment data, the knowledge that can be acquired by analysing data from hundreds of plants will easily outpace the knowledge held by any single plant or supplier. This gives rise to large information asymmetries - where some parties know a lot more than others – and this impedes trust. Therefore, all parties will use different strategies to safeguard the relationship. Suppliers are likely to restrict the level of standardization, whilst buyers are likely to restrict access to equipment data from their plant. Moreover, IT-security acts as an additional risk to be managed, on top of what can be accounted for by using non-technical means, such as formal contracts and credible commitments. In particular, it is not primarily a safeguard between contracting partners such as buyers and suppliers, but more so a safeguard against infringement from actors that are independent to the relationships. In practice, this lack of trust makes manufacturing plants reluctant to implement connectivity in their equipment and to start sharing data with suppliers. Therefore, before value can be created and traded on the basis of consolidated equipment data, these sources of mistrust must be overcome.

Environmental contingencies

Environmental contingencies can be aspects of the external business environment or the internal task environment that influence the adoption of certain technologies, processes and structures. In principle, maintenance managers carefully analyse the external environment, take into consideration the internal characteristics of their plant, and try to adapt their organization accordingly. With respect to Smart Maintenance, the most important environmental contingency, as evident in the definition, is pervasiveness of digital technologies. Digital technologies are everywhere, and Smart Maintenance is the organizational response to this contingency. In addition, a particular facet of viewing digitalisation as an environmental contingency is that it represents not just rapid technological change in general, but a shift between technologies from analogue to digital. A specific characteristic of distinct technological shifts is that they are *skill-biased*: they alter the labour demand and returns to certain types of skills. Typically, new technologies increase the relative demand for more educated and highly skilled workers. However, the challenge right now is that the skills that are becoming increasing valuable are not available on the labour market. Most plants are desperately searching for people who have the right contemporary skills set to make use of digital technologies, but they are nowhere to be found.

Institutional isomorphism (coercion and mimicry)
The adoption of Smart Maintenance can also be driven by *institutional isomorphism*: doing what everyone else is doing. In times of rapid change and high uncertainty, it is very difficult for maintenance managers to find answers to the best way of adapting their organization. Therefore, instead of carefully examining contingencies, managers are likely to find the answers by means of *coercion* and *mimicry*. Coercion – acting on pressures from other organizations or societal expectations – can for example be when suppliers dictate the use of certain technologies as a requirement to uphold the relationship. Mimicry – imitating others who seem to be successful – can for example be when managers are searching for the current trends and try to model their organization based on success stories from other plants. This means that maintenance functions might not adopt Smart Maintenance because they have evidence of its effectiveness, but rather because they are being coerced to do it, or because they are mimicking others who are doing it.

Performance

Performance is the outcome of fit: achieved internal and/or external fit is rewarded with better performance, whilst misfit is penalized with worse performance. Smart Maintenance is posited to lead to various performance benefits at the plant- and firm-level. In this section, the important dimensions of performance are only briefly introduced and are not covered in depth. For extensive descriptions of these dimensions, please refer to Section 4 in appended paper C.

Plant performance (maintenance, manufacturing, safety, environment)
The primary performance outcome of Smart Maintenance is *maintenance performance*: that the maintenance function efficiently and effectively achieves its objectives, for example, as manifested in longer durations between failures, shorter repair lead times, conformance quality of maintenance work and cost-effectiveness. Increased maintenance performance in turn improves *manufacturing performance*: products are produced as intended in a swift and even flow, that is, production with e.g. faster throughput times, higher delivery precision and lower amounts of scrap. Moreover, increased maintenance performance is also expected to contribute to *safety performance* and *environmental performance*: e.g. avoiding safety hazards by reducing the amount of reactive work under pressure of time, or reducing energy consumption and emissions from equipment breakdowns.

Firm performance (financial performance, competitive advantage)
It is plausible that Smart Maintenance also contributes to the two primary performance dimensions at the level of the firm: *financial performance* and *competitive advantage*. Especially in manufacturing plants with automated production and high mass output orientation, equipment downtime can be extremely costly and thereby directly linked to profitability. However, in general, the relationship between a plant's maintenance practices and a firm's financial performance is difficult to isolate, because many aspects that determine financial performance are often uncontrollable by the plant (e.g. sales volume). A way of thinking about this link is that, for example, if the maintenance function contributes to high equipment availability, which in turn enables a reduction of throughput times at unaltered unit cost, this increase in productivity is likely to be linked to higher profits for the firm. Similarly, a manufacturing firm's competitive advantage is influenced by many aspects that are not directly related to operations, e.g. specific product features or unique after-market services. Still, it is possible that in certain business environments where manufacturing firms compete with regard to productivity, maintenance can be an important complement for competitive advantage.

Contingency model

In order to gain a more holistic understanding of how all of these variables are related, a contingency model is specified (Figure 6 in appended paper C). The full model is targeted towards a scholarly audience, so as to guide further empirical research on Smart Maintenance. To simplify the interpretation of the model for a practitioner audience, the three types of variables (context, response, performance) can be categorized into three boxes with three connecting arrows (Figure 8).

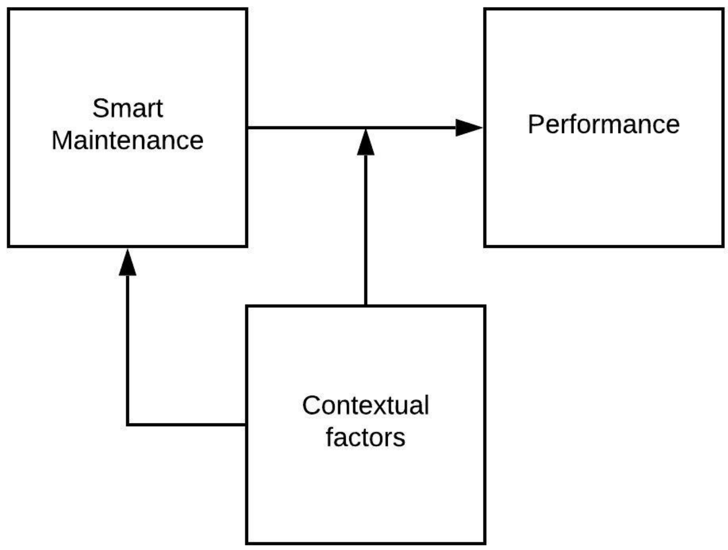

Figure 8. Simplified contingency model

The first box, "Smart Maintenance", represents the four dimensions that maintenance organizations can achieve – it is "what we do". The second box, "Performance", represents the dimensions of performance at the plant- and firm level – it is the "results of what we do". The third box, "Contextual factors", represents the internal and external factors that influence plants to adopt Smart Maintenance and the difficulty with which it can be implemented, as well as what determines whether some plants will receive more benefits than others – it is "what influences what we do and the results of what we do".

This simplified model makes it possible for practitioners to engage in contingency thinking without getting lost in the details. The model provides guidance for developing strategies aimed at implementing Smart Maintenance. Firstly, such strategies should focus on a joint, co-ordinated implementation of all four dimensions of Smart Maintenance. Focussing solely on one of the four dimensions could be a waste of resources, or even have a detrimental effect. Secondly, to ensure implementation success it is critical to also consider the entire range of necessary investments, facilitate a supporting corporate culture and dedicated leadership, and structure efficient interfaces with external parties. It is especially important to consider the contextual factors when facing extensive implementation lags. Thirdly, and finally, to assess the benefits it is advised to monitor a wide range of performance implications, both within and beyond the maintenance function. Performance can be increased even more by leveraging the contextual factors.

4.2.4 *Interim discussion*

Above all, the results from Study II achieves concept clarity with respect to Smart Maintenance. The four dimensions provide practitioners with a useful and action-inspiring conceptualization that enables them to easily understand what Smart Maintenance is. Moreover, the elaborated concepts and their relationships, as illustrated in the contingency model, provide practitioners with a holistic understanding of Smart Maintenance. Understanding not only what Smart Maintenance is, but also its associated implementation issues and performance benefits, enables industrial managers to develop policies and strategies for successful implementation of Smart Maintenance.

The results also serve as a research agenda for industrial maintenance management. It is hoped that this agenda will inspire scholar-to-scholar communication that is centred around empirical research on Smart Maintenance. If maintenance scholars pursued the agenda by means of both exploratory and confirmatory work, the knowledge within the research field could be greatly advanced. Of particular value is providing valid prescriptions of successful actions to practitioners and policy-makers.

With the results from Study II at hand, it is reasonable to look back and reflect on the relationship to Study I. The scenario planning results were placed in my bank of knowledge and experience rather than used as direct input to the conceptualization of Smart Maintenance. However, seen together, both Study I and Study II are centred around anticipating what *we*, scholars and practitioners within industrial maintenance management, *need to know*. The best way of "predicting the future" is to influence the conversation about what it could or should be, so as to stimulate cumulative research efforts, as well as to support reflective practitioners in their own development efforts (Corley and Gioia, 2011); in other words, creating desirable futures (Simon, 1996). Therefore, the two studies represent the progression of understanding more about phenomena, where it is completely natural to reduce a large set of plausible events (Study I) into a smaller set of clear, distinct concepts (Study II). To exemplify how the two studies are connected without me as the natural link, the eight probable scenarios (Table 2 in Section 4.1.3) can easily be placed in the boxes of the contingency model (Figure 6 in appended Paper C). *Data analytics, big data management, fact-based maintenance planning* and *maintenance planning with a system's perspective* would collapse into the *data-driven decision making* dimension; *interoperability* into *openness* within the interface context; *education and training* into *complementary investments* within the investment context; *smart work procedures* into the interaction between *data-driven decision making* and *external integration*; and *environmental legislation and standards* into *environmental contingencies* or *institutional isomorphism*. The same exercise could in principle be made with respect to all 34 projections.

With respect to the next step, conceptualization is naturally followed by operationalization. By clearly describing and formally defining Smart Maintenance and its four dimensions, the concept is now in a suitable position to be operationalized. That brings us to Study III.

Table 5. Summary of results related to RQ2

- Focus groups and interviews were conducted with over 100 participants, representing more than 20 different firms.
- Data structures were created from the qualitative data.
- The identified conceptual variables include Smart Maintenance, performance and contextual factors.
- Conceptual definitions of Smart Maintenance and its four underlying dimensions are developed.
- The concept structure of Smart Maintenance is modelled.
- A complete contingency model specifies the relationships between concepts.
- A research agenda for industrial maintenance management is proposed.

4.3 RESULTS: OPERATIONALIZATION OF SMART MAINTENANCE

This section presents the results from study III that are related to RQ3.

4.3.1 *Introduction*

Owing to the concept clarity achieved in Study II, it is now evident that implementing Smart Maintenance in manufacturing plants implies adopting the four dimensions of *data-driven decision-making, human capital resource, internal integration*, and *external integration*. In order to stimulate the implementation of Smart Maintenance by removing barriers to adoption and/or providing valid prescriptions of suitable implementation strategies, a measurement instrument is needed that can empirically measure Smart Maintenance in manufacturing plants.

Therefore, the aim of this study is to develop an instrument for measuring Smart Maintenance. Following on from the conceptualization of Smart Maintenance, the concept is now suitable to be operationalized in the form of developing a psychometric measurement instrument. Study III consists of generating items to represent the constructs, assessing content validity, collecting data for empirical pilot testing, and assessing the factor structure. The instrument can be used by scholars to measure the adoption of Smart Maintenance and to link this to performance. It can also be used by practitioners to assess, benchmark and longitudinally evaluate Smart Maintenance in their organization.

4.3.2 *Methodology*

Detailed methodological descriptions are provided in Section 3&4 in appended paper D. Because of the task nature of creating measurement instruments, the appended paper is heavy on psychometric methodology. The processes of developing and evaluating such instruments are not well-known to maintenance practitioners. Yet, in order to gain practitioners' trust in using the instrument, as well as interpreting and acting upon its results, it is important to facilitate a general understanding of how psychometric instruments are created. Therefore, the content of the appended paper is here described using a manufacturing analogy that is understandable to a broader audience. Specifically, the instrument that measures Smart Maintenance was made in a production process consisting of several sequential steps, as illustrated in the value stream mapping in Figure 9.

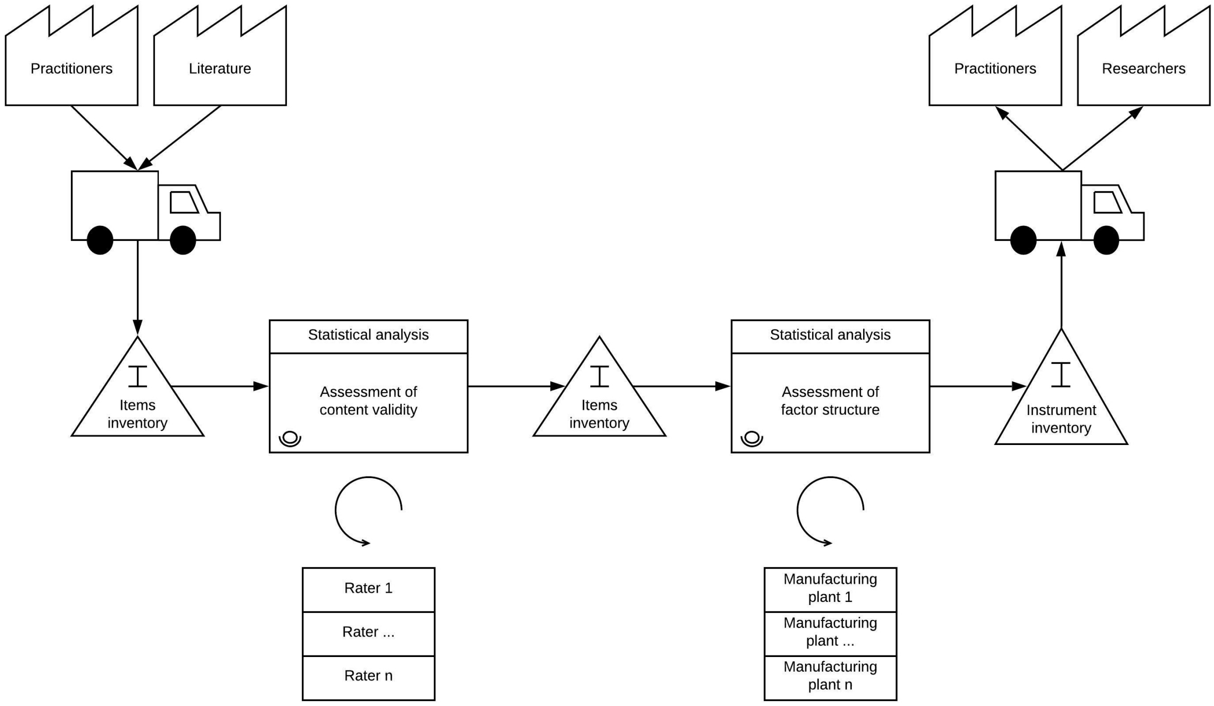

Figure 9. Production process for the measurement instrument

Figure 9 illustrates the production process from initial supply to final delivery. The raw material to produce the instrument consists of *items* – questions that capture the essential aspects of the four dimensions of Smart Maintenance. A large pool of items was created by practitioners, as well as drawn from the literature. After an initial screening and refinement of the raw material, the items were placed in the first items inventory. Thereafter, the items were processed through the *assessment of content validity*, which checks whether the items are good representations of the constructs. The data used in this process was pulled from industrial and academic representatives, who also rated the correspondence between the items and the conceptual definitions of the four dimensions. By means of statistical analysis using ANOVA, the content validity of each item could be tested. The items with approved content validity were placed in the second items inventory, whilst the non-conforming items were scrapped. Thereafter, the most highly ranked items from each dimension were processed through the *assessment of factor structure*. The data used in this process was pulled from a set of manufacturing plants, in the form of answers to questions about Smart Maintenance at their plant. By means of statistical analysis using PA and ML-based EFA, the factor structure of the instrument could be tested. The evaluated and refined instrument was thereafter placed in the final inventory, ready to be shipped to practitioners for industrial use and to researchers for further testing and scientific use.

4.3.3 *Results*

The results from the different steps of the production process are presented in this section, focussing on further illuminating how the large pool of items was transformed into a useful measurement instrument. In the first step, a total of 455 items were generated from practitioners and the literature. A total of 50 individuals from manufacturing plants and industrial service were instructed to generate items that are well understood by themselves, which resulted in a list of 366 items. Moreover, by taking inspiration from existing empirical research and measures of similar constructs in the literature, an additional 89 items were generated so as to achieve a comprehensive pool with roughly equal numbers of items for all four dimensions. Since 455 items are much more than what is needed to produce the final instruments, an initial item pool reduction was made to achieve a set of 80 clearly structured and well-written items (see Table 1 in paper D).

Thereafter, the purpose of assessing content validity is to ensure that all items in the instrument represent its intended content, and equally important, do not represent any unintended content (MacKenzie et al., 2011). In other words, for every item, the correspondence to its targeted dimension of Smart Maintenance should be high, and the correspondence to the other dimensions should be low. Statistically, this translates into first testing whether an item's mean rating in one dimension *differs* from its rating in other dimensions, followed by testing whether the mean rating in the targeted dimension is *higher* than the mean rating in all other dimensions (Hinkin and Tracey, 1999). In order to conduct this test, a total of 42 individuals from industry and academia rated the extent to which the 80 items capture each of the four dimensions of Smart Maintenance using 5-point Liker scales (see Figure 4 in the appended paper for an illustration of the rating task). This data set was analysed using one-way repeated ANOVAs and t-tests, which serve to assess the content validity of each item (Hinkin and Tracey, 1999) (see Table 1 in paper D for detailed results). From the results, a total of 11 items were found to have inadequate content validity. These items confounded with the meaning of two dimensions. For example, some items from the human capital resource dimension overlapped with the internal integration dimension. They are not good representations of the constructs and may contribute to a contaminated measurement instrument, and were therefore scrapped. The remaining 69 items are all good representations of their intended dimension of Smart Maintenance.

After content validity has been assured, the next step is to test whether the instrument works in reality. The general purpose of assessing the factor structure is to find a useful factor model that fits data well. In other words, the statistical model that represents the instrument should explain the correlation among items in a manner that is consistent with what it intends to measure (Brown, 2006). Statistically, and specifically for new instruments, this translates into deploying an iterative approach to exploring the dimensionality of the data set and testing the factor structure (Schmitt, 2011). In order to conduct this pilot test, sample data from a total of 59 manufacturing plants were collected. The 48 most highly ranked items from the content validity assessment were used in the pilot (12 from each dimension), where each item was measured using 5-point Likert scales. The data set was analysed using PA and ML-based EFA, focussing on testing factor models for each dimension of Smart Maintenance separately, as well as a factor model that combines all four dimensions. On the basis of multiple statistical criteria, the overall results indicate that the separate models, as well as the combined model, fits well (see Table 4 and Table 5 in the appended paper for details). Specifically, all models have good global fit (χ^2-test, F-test) and approximate goodness-of-fit (RMSEA, CFI, SRMR), as well as acceptable psychometric properties such as significant factor loadings, high construct reliability, strong factor determinacy, and adequate range of factor correlations. The four separate models fit well using 8-11 items per construct, and the combined model fits well with a total of 24 items. This combination of items represents the measurement instrument.

4.3.4 *Interim discussion*

The output from the production process in Figure 9 is an instrument that can be used to measure Smart Maintenance in manufacturing plants. The appended paper is targeted towards a scholarly audience with a focus on disclosing the process for developing the instrument. In a typical research setting, the instrument can be used in survey research to collect data from a large sample of manufacturing plants, followed by using sophisticated and technical methods, such as factor analysis, to compute a single score in each dimension of Smart Maintenance for each plant. Here, the scores are termed *refined factor scores* – linear combinations of the observed variables that take into consideration what is shared between the items and the factor (i.e. shared variance) as well as what is not measured (i.e. measurement error). A valid and reliable instrument ensures that the factor scores are accurate representations of the position of each plant with regard to the latent variables. The factor scores can then be used to evaluate how different constructs are related to each other. For example, the scores for the four dimensions of Smart Maintenance can be entered together with measures of performance in a structural equation model, which enables testing the impact of Smart Maintenance on performance.

The same instrument can be used by practitioners to assess, benchmark and longitudinally evaluate Smart Maintenance in their organization, but the procedure is slightly different. A manufacturing plant can use e.g. a self-administered questionnaire to collect data on the items, followed by calculating the corresponding factor score. While refined factor scores are most accurate, the disadvantage is that they are complex to compute. In a practical setting, it is most realistic to compute the factor scores without sophisticated statistics. The validity and reliability of the instrument serves as evidence to know that it is acceptable to also use the items standalone, without the factor structure. Here, the scores are termed *non-refined factor scores*. The simplest way is to calculate the average of the raw scores on all the items that load on each factor. This enables the scores of several factors to be compared, even if there are different numbers of items per factor. For example, the one-factor model for data-driven decision-making consists of 8 items, while the corresponding model for human capital resource consists of 11 items. This type of factor scoring is suitable for maintenance practitioners because it is very easy to compute and interpret. However, these scores are not as accurate as refined factor scores because they do not separate the shared variance from the unique variance, give equal weight to all items, or consider cross-loadings with other constructs. Still, when used in this type of practical setting, it is questionable whether the difference in accuracy between refined and non-refined factor scores would significantly alter how practitioners interpret and act upon the results.

Therefore, providing answers to the items in the instrument allows practitioners to assess Smart Maintenance in their organization. By computing simple factor scores, each plant receives a result that corresponds to their position in the four dimensions. This serves to identify improvement potentials with respect to Smart Maintenance. Moreover, practitioners can use the scores for benchmarking, for example by comparing against an industry average or the number of plants that score better or worse than themselves. Finally, by assessing Smart Maintenance repeatedly, practitioners can track changes over time, in order to evaluate whether there has been any progress towards Smart Maintenance or not.

Table 6. Summary of results related to RQ3.

- A pool of 80 items was generated that captures the four dimensions of Smart Maintenance.
- By means of an ANOVA approach, a total of 69 items were found to have adequate content validity.
- Using data from 59 manufacturing plants, a total of 48 items were evaluated in a pilot-test.
- Four one-factor EFA model with 8 to 11 items per construct demonstrate good model fit and psychometric properties.
- One four-factor EFA model with 24 items demonstrate good model fit and psychometric properties.
- The instrument can be used by both scholars and practitioners.

5

GENERAL DISCUSSION

This chapter provides a general discussion of the results in a broad context, followed by answers to the three research questions. Furthermore, this chapter discusses the academic and practical contributions of the thesis. Finally, a proposal for future work is provided.

By means of three empirical studies, this thesis has contributed to achieving a holistic understanding of Smart Maintenance. Specifically, Study I developed future scenarios for maintenance in digitalised manufacturing; Study II conceptualized Smart Maintenance; and Study III operationalized Smart Maintenance. Before providing answers to the research questions, the results from the three studies are discussed in relation to existing research within maintenance management, operations management and psychometrics, so as to position the thesis with respect to present knowledge (Section 2). Note that since I see this thesis as a linear sequence where I progressed, learned and improved over time, I do not provide a synthesis for how the separate findings of three studies add up to a distinct whole. Instead, I provide answers to the research questions one by one, and again stress that the fullest understanding of the research will be achieved by viewing it is as a process in several interconnected steps.

5.1 POSITIONING THE THESIS – WHERE DOES IT FIT?

The discipline of industrial maintenance management consists of a multitude of topics, a variety of research methods, and a diverse set of perspectives on the world. It is therefore important to position this thesis relative to existing maintenance research (Section 2.2).

Above all, the research in this thesis is complementary rather than competing. On one hand, most of the important concepts in this thesis are also studied and recognized by other maintenance researchers. There exists plenty of research within each of the four dimensions of Smart Maintenance, respectively. Data-driven decision making has been a core topic within maintenance research since the inception of ICT (Lee et al., 2006; Muller et al., 2008), and it remains as arguably the primary topic of contemporary research (Lee et al., 2015; Roy et al., 2016; Vogl et al., 2016; Ruschel et al., 2017). Similarly, integration of maintenance has also been a key topic for years, focussing on exchange of data, information and knowledge between maintenance and both internal and external parties (Jonsson, 2000; Liyanage and Kumar, 2003; Muller et al., 2008; Candell et al., 2009; Aboelmaged, 2015). Moreover, human capital resource is recognized as a key challenge for maintenance in digitalised manufacturing (Dworschak and Zaiser, 2014; Weiss et al., 2016), and most of the contextual variables of Smart Maintenance, as well as the 34 projections, are also mentioned in existing literature (Weiss et al., 2016). More specifically, the results from Study I largely overlap with the results in Akkermans et al. (2016). Although conducted independently, the two studies deployed in principle the same research design to study the same phenomena, at the same time, and yielded similar results. In addition, Roda et al. (2018) replicated the results from Study I within the Italian manufacturing industry, finding support for all eight probable scenarios, as well as two out of three wildcard scenarios. In this regard, this thesis aligns well with the main topics within the field of industrial maintenance management and largely corroborates the advancements made within the field over the past decades.

On the other hand, the thesis provides a different perspective on the concepts of interest as well as a different way of organizing the body of knowledge. The main difference lies in the research being *phenomenon-driven*. This type of research does not replace practical problem solving or theory-driven research, it is complementary. Whilst there has been tremendous progress in maintenance research focussing on technology development, this thesis allows for a holistic view on a phenomenon that is rooted in the interest of practitioners. This tends to be forgotten when focusing on existing research objects (Von Krogh et al., 2012). In addition, instead of treating each concept as a separate topic, this thesis provides a holistic understanding that integrates an entire range of hard and soft dimensions. Social phenomena have unique characteristics that make it almost impossible to approach them in a theory-driven, reductionist manner. Each element influences the whole system and must be understood in this way (Daft and Lewin, 1990). Moreover, the social science view has had a major influence on the research (Holweg et al., 2018), which is especially evident in how Smart Maintenance is explicitly constructed and modelled as a “social science concept” (Goertz, 2006; Podsakoff et al., 2016). This differs from the traditional meaning of concepts in maintenance research (Sherwin, 2000; Pintelon and Parodi-Herz, 2008), and this invites new research directions for the field. In particular, this systematic way of approaching a phenomenon enables a research field to more clearly distinguish aspects of the phenomenon, propose and select theories, and conduct research using a larger variety of methods (Von Krogh et al., 2012). Calls for this type of holistic maintenance research have existed for decades but have struggled to gain major traction (Coetzee, 1999; Tsang, 2002; Bengtsson and Salonen, 2009). Furthermore, the conceptualizing and operationalizing of Smart Maintenance allows the research field to pursue rigorous empirical research, which represents a much-needed advancement of the field as a whole (Veldman et al., 2011; Fraser et al., 2015). In other words, while there exists a plethora of technological tools, methods, techniques and approaches for maintenance in digitalised manufacturing, this thesis contributes a better understanding of these phenomena in real industrial settings.

Aside from the field of industrial maintenance management, much of the inspiration for the research in this thesis has come from existing OM research (Section 2.3). The socio-technical view is clearly reflected (Holweg et al., 2018), such as the systems model in Paper A, and the holistic view on internal and external integration is largely aligned with OM literature (Barki and Pinsonneault, 2005; Flynn et al., 2010; Schoenherr and Swink, 2012). The notion of fit is central to the conceptualization of Smart Maintenance in the form of both alignment and configuration (Sousa and Voss, 2008). Moreover, the empirical side of OM has been a large source of content inspiration, such as searching for drivers of performance (Ketokivi, 2016) and macro topics (Pilkington and Meredith, 2009), as well as methodological inspiration such as borrowing theories from other disciplines (Holweg et al., 2018) and using a variety of research designs and methods (Boyer and Swink, 2008; Singhal et al., 2008). In addition, phenomenon-driven research has a long tradition in management and organization science and has generated breakthrough knowledge that has reshaped the scientific discourse (Von Krogh et al., 2012).

The thesis has also adopted a measurement approach from other fields in the form of psychometrics. Although latent variable modelling and statistical techniques such as factor analysis are widely used in a variety of adjacent disciplines (MacKenzie et al., 2011), including OM (Ketokivi and Schroeder, 2004; Roth, 2007), it is fairly uncommon within maintenance research. By bringing these methods into the field, it is hoped that maintenance researchers can become more equipped with powerful methods for empirical research. This in turn, can stimulate increasing attention to building, elaborating and testing theories that provide valid predictions and explanations for the behaviours of various maintenance concepts of interest.

5.2 ANSWERING THE RESEARCH QUESTIONS

The holistic understanding of Smart Maintenance was achieved by means of three empirical studies (Study I-III) that provide answers to three research questions (RQ1-3). Within this thesis there is no higher order synthesis or complex relationship between the studies. It simply represents me learning about phenomena throughout the journey as a PhD student. Consequently, answers to the three research questions are provided one by one:

RQ1) What future scenarios can be expected for maintenance in digitalised manufacturing?

The future of maintenance is likely to be affected by changes along both hard (technical) and soft (social) dimensions (paper A). A total of 34 projections can describe potential changes to the internal and external environment of maintenance in digitalised manufacturing. From these projections, eight dominant themes can be expected: data analytics, interoperability, big data management, education and training, fact-based maintenance planning, smart work procedures, maintenance planning with a systems perspective, and stronger environmental legislation and standards.

RQ2) How can Smart Maintenance be conceptualized?

Smart Maintenance is defined as an "organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies", and consists of four core dimensions: data-driven decision-making, human capital resource, internal integration and external integration (paper B). Furthermore, differences in the adoption of Smart Maintenance are likely to be explained by motives to achieve internal and external fit, as well as by implementation issues related to change, investments and interfaces. Finally, Smart Maintenance is expected to have implications on multiple dimensions of performance (paper C).

RQ3) How can Smart Maintenance be operationalized?

Smart Maintenance is operationalized by means of an empirical measurement instrument (paper D). The instrument has acceptable validity and reliability and can be used to assess the four dimensions of Smart Maintenance in manufacturing plants. It can be used by practitioners to assess and benchmark Smart Maintenance in their organization, and it can be used by researchers to study differences in the adoption of Smart Maintenance and link these to differences in performance.

5.3 WHY "SMART MAINTENANCE"?

Smart Maintenance is obviously the focal concept in this thesis, and some people are inevitably going to comment on the choice of the term "Smart Maintenance". I fully understand that it might be tempting to dismiss this as just another buzzword, or another in a long line of management fads. In practice, some maintenance managers are probably going to tear their hair out and think "No! Not another maintenance concept, we spent years trying to implement TPM!". In academia, some might argue that hardcore scholars should do everything in their power to shy away from anything that resembles such follies. I have a completely different perspective. First of all, we could have called it something else, but we did not. The interest for Smart Maintenance is phenomenon-driven – it focusses on an observed phenomenon that practitioners are interested in. Locally in Sweden, the most widely used term to communicate ideas about maintenance in digitalised manufacturing is indeed Smart Maintenance. The logical scholarly starting point is therefore to draw from the real world and the experience of working professionals. Research that focusses on concepts that are rooted in practice is more likely to capture the engagement of practitioners, simply because it relates to their everyday problems and helps them get better at what they do.

Moreover, the term in itself is important because *language matters immensely*. Language makes it possible to categorize and interpret the world, structure our ideas and express them in interactions with each other. Language also acts as a tool for developing our thoughts and to collect, store and use knowledge. In fact, the development of new language and terminology that enables scholars and practitioners to express, exchange and consolidate ideas is a crucial part of phenomenon-driven research (Von Krogh et al., 2012). Therefore, the term Smart Maintenance serves a critical cognitive function in the form of the common, collective term we use for communication and collaboration. After all, there is almost always one conceptual term at the top of the pyramid. This term appears in models, propositions and theories. While the term itself does not necessarily hold any causal power, its constitutive elements do (Goertz, 2006). For example, it is called "lean production", but it is the reduction of the seven wastes that make firms more productive (Womack et al., 1990). Similarly, it is called a "welfare state", but it is unemployment compensation, old age pensions, health insurance and workman's compensation that provide the benefits to its citizens (Goertz, 2006). In this case, it is called "Smart Maintenance", but it is data-driven decision-making, human capital resource, internal integration and external integration that make maintenance functions perform better. Still, without the collective terms that keep the elements together, scholars and practitioners would be lost in translation.

5.4 ACADEMIC AND PRACTICAL CONTRIBUTIONS

The general discussion section of an engineering thesis usually explains how the results from different studies or papers are related to each other, as well as provides separate discussion sections for methodological limitations, academic contributions and practical contributions, respectively. However, I see the main point of the general discussion section as the opportunity to argue for why I am entitled to claim what I do, and to reflect upon what I have learned along the way. Therefore, I choose to discuss the academic and practical contributions of this thesis in relation to three questions about the quality of scientific work (Antonakis, 2017). Firstly, "So what?" answers whether the research is original and important to practice so as to be capable of contributing to cumulative research efforts. This is about *relevance*. Secondly, "Is it rigorous?" answers whether the research is robust, accurate and credible. Obviously, this is about *rigor*, and this section corresponds to the more typical methodology discussion. Thirdly and finally, “Will it make a difference?” answers whether the research is capable of informing policy and practice. This is ultimately about *usefulness*. Each of these three questions are discussed under separate headings. Thereafter, I also discuss the progress of scientific quality across the three studies, as well as my personal development as a researcher. Connecting back to the research approach in Section 3, I hope that this discussion section can serve as a means for doctoral students, practitioners and policy-makers to understand the value of empirical research, as well as the importance of long-term investments in doctoral education that stress a continuous increase in the quality of scientific work.

5.5 SO WHAT?

Theoretical advancement of a scientific discipline involves a push-pull dilemma between two opposing forces: *fragmentation* and *lack of novelty* (Fisher and Aguinis, 2017). On one hand, new, creative ideas can lead to novel frontiers, but also confusion and lack of clarity. On the other hand, consolidating known ideas can deepen our understanding, but also just be “old wine in new bottles”. I have tried to navigate this dilemma by largely focussing on *theory elaboration* – “the process of conceptualizing and executing empirical research using pre-existing conceptual ideas or a preliminary model as a basis for developing new theoretical insights by contrasting, specifying, or structuring theoretical constructs and relations to account for and explain empirical observations” (Fisher and Aguinis, 2017)(p. 4). In simple terms: theory elaboration combines the old with the new, so as to make theory more useful. In fact, a holistic approach to phenomenon-driven research implies not only identifying new phenomena, but also putting them against the backdrop of already known phenomena (Von Krogh et al., 2012). More specifically, the relevance of a phenomenon hinges on its *generality* and *uniqueness* (Von Krogh et al., 2012). With respect to generality, Smart Maintenance impacts the status quo of industrial maintenance management by changing the way maintenance is organized and executed at the level of individuals, groups, plants, firms and industries. With respect to uniqueness, Smart Maintenance challenges prevailing knowledge about maintenance in both industry and academia by changing institutions, assumptions and norms. For this type of phenomena, a small amount of new is often a real achievement. Even if the research only comes up with something that is a little bit new, ideas produce ideas in such a way that even a tiny bit of novelty might lead to something with a lot more. In other words, this thesis integrates both novel and existing ideas about maintenance management, so as to create a clear, understandable, and holistic understanding of Smart Maintenance.

Study I (Paper A) contributes theoretically in the form of identification and verification of phenomena that are important to practice and suitable as subjects for empirical research. By combining literature with focus groups and interviews to develop the 34 projections, a mix of both novel and existing phenomena could be identified that are anchored in both the existing literature and the interest of practitioners. Furthermore, the Delphi-study verified that the 34 projections are relevant to practice by soliciting industrial maintenance experts to classify them as probable, impactful and desirable. Moreover, the development of eight probable scenarios and three wildcard scenarios provided more in-depth understanding of the phenomena themselves, as well as additional insights into practical challenges with respect to their implementation. All 34 projections thereby constitute legitimate objects for cumulative research efforts. In order words, research that builds on the results from this study will be asking the right questions.

Study II (Paper B & C) is firmly anchored in practice. Instead of being driven by gaps in the literature, the study focused on addressing contemporary and future questions that are relevant to maintenance practitioners. This is a particularly useful approach for uniting research and practice (Von Krogh et al., 2012). From the perspective of originality, the study provides novel theoretical advancement of two kinds. Firstly, the conceptualization of Smart Maintenance contributes with *concept specification*: specifications and/or refinements that more accurately reflect the realities and insights that emerge empirically (Fisher and Aguinis, 2017) (p. 9). This includes both identifying and defining concepts that have not been previously considered, as well as refining already existing concepts. The development of conceptual definitions for Smart Maintenance and its four dimensions represents a mix of defining new concepts and refining the definition of existing concepts for the specific context of plant maintenance. Above all, the results bring concept clarity with respect to Smart Maintenance. For practitioners, this means that Smart Maintenance is now clear, easy to agree upon and possible to act upon. For researchers, it means that it is now possible to operationalize Smart Maintenance and make it subject to theory testing.

Secondly, the study also contributes with *concept structuring*: elaboration of theoretical relations so that they accurately describe and explain empirical observations (Fisher and Aguinis, 2017) (p. 11). This includes both identifying and describing specific relationships that have not been previously known, or describing mechanisms underlying known relations. The Smart Maintenance concept structure (Figure 5 in Paper B) describes the nature of relationships between the four dimensions, i.e. that they constitute a configuration of four complementary organizational states. The contingency model (Figure 6 in Paper C) provides the overall concept structuring with respect to contingencies, responses and performance. Moreover, the empirical observations and theoretical interpretations provide further descriptions of the specific relationships and plausible underlying mechanisms within the models. These models and descriptions thereby provide researchers with clear guidance for further theory building and theory testing. Overall, the results from Study II improve the validity and scope, as well as explanatory and predictive adequacy of theory with respect to Smart Maintenance by increasing the accuracy of concepts and more clearly distinguishing between different concepts (Fisher and Aguinis, 2017). In summary, all the concepts in the models hold causal powers and relate to pressing managerial problems.

Study III (Paper D) contributes by linking the conceptual to the empirical; specifically, making Smart Maintenance observable and measurable by means of a psychometric measurement instrument. This is relevant to both researchers and practitioners. For researchers, it enables the measurement of differences in adoption of Smart Maintenance and links this to differences in performance. In other words, researchers can use the instrument to test whether plants that work with Smart Maintenance perform better than those that do not. In the name of relevance, this is essentially what every maintenance manager wants to know. Moreover, the instrument can be directly used by practitioners to assess, benchmark and longitudinally evaluate Smart Maintenance in their organization. With respect to originality, the study demonstrates a series of construct measurements and validation procedures that are highly relevant to advance the state of empirical research within the maintenance field. While these procedures have long traditions within considerably more mature disciplines, such as strategy, organization, psychology and marketing, they are rarely used within the maintenance field. The study thereby illustrates the value of taking inspiration from the scientific craftsmanship of other disciplines, and it is hoped that the results will stimulate more useful empirical research within the maintenance field.

5.6 IS IT RIGOROUS?

Rigor is relative - it is evaluated against a standard of some kind. I wish there was a set of robust, unequivocal absolute measures to evaluate rigor, but there is not. Instead, the standards for assessing research are usually field-specific. In fact, the process of developing, maintaining and disrupting the standards for what constitute legitimate scientific inquiry is one of the defining characteristics of a field. Moreover, the requirements for rigor are different for every research method, and rigor in phenomenon-driven research requires both adherence to existing standards and willingness to change the definition of rigor as the knowledge about the phenomenon accumulates (Von Krogh et al., 2012). The problem here is that what is determined to be good in the face of relative measures might not actually be so. The mind-set I have adopted to ensure the rigor of my research is actually quite simple. First is the pragmatic aspect: as long as I compare my work against standards that are higher than those currently held within my own field, I should be fine. The main idea is to not let the standards of my field limit my work. Second is the pursuit aspect: I simply focus on constantly searching for the right questions to ask and the right problems to solve; gradually learning how to better observe and explore phenomena; continuously developing my skills in categorizing and quantifying variables so as to enhance our understanding of them.

Study I (Paper A) carefully followed the established criteria for rigor in Delphi-based scenario planning (Nowack et al., 2011). In particular, the study deployed a standardized procedure for expert selection (van der Gracht and Darkow, 2010), incorporated the four characteristics of the RAND method (Dalkey and Helmer, 1963), conducted an extensive three-round Delphi study, and evaluated the presence of desirability bias (Ecken et al., 2011). The study thereby fulfilled the vast majority of explicit criteria that exist for ensuring the validity and reliability of this type of research.

Study II (Paper B&C) is more difficult to assess with regard to rigor. Unlike the range of formal criteria that exist for different types of statistical methods, there is no consensus on a set of criteria to evaluate qualitative research. Attempts to develop such criteria for qualitative research have largely failed, in part because different approaches to qualitative research are based on a variety of, and less obvious, philosophical assumptions (Pratt, 2008). In order to ensure the rigor of Study II, three main strategies were used. Firstly, acknowledging that theories are constructed and that all researchers do not see the same things, the study used a set of general theories in order to seek and choose the best theoretical interpretations for the empirical observations (Mantere and Ketokivi, 2013). Secondly, the empirical generalizations were transparently described, so as to illustrate the cognitive role of the researchers in creating the concepts and their proposed relationships (Aguinis et al., 2018). Thirdly, unbiased generalizations were strived for by means of careful coding principles and various forms of external audits (Gioia et al., 2013).

Study III (Paper D) followed a set of recommended best-practice approaches for construct measurement and validation (MacKenzie et al., 2011). Essentially every single step of the study was executed in accordance to established criteria for rigor, with a particular emphasis on the early, fundamental steps of the process. These initial steps are critical to the success of later steps, but they are often ignored. These include assessing concept-measure consistency (Goertz, 2006), quantitatively assessing content validity from the respondent perspective (Hinkin and Tracey, 1999), and using a holistic statistical approach to assess the factor structure of the instrument (Schmitt, 2011).

5.7 WILL IT MAKE A DIFFERENCE?

Usefulness is the holy grail. All research should, in one way or another, sooner or later, make a difference and have an impact on society. Otherwise it is a waste of researchers' time and taxpayers' money. In this digital day and age, practitioners are turning to the academic community for help. It is our duty to offer prescriptions of successful actions backed by science. Phenomenon-driven research ranks highest in terms of practitioners' interest, because searching for and investigating important phenomena is crucial to help practitioners succeed in an increasingly complex world (Daft and Lewin, 1993). However, the traditional and most common measure of scholarly impact is the number of citations in papers published in academic journals. Everyone knows that this is not a direct measure of usefulness because it only captures the *internal* impact on the academic community. Still, such measures are important because most researchers aspire to influence the work of other researchers. The *external* impact can be understood as the influence research has on policy and practice, and this is more akin to the true meaning of usefulness (Aguinis et al., 2019). External impact can be reflected in e.g. invitations to and presentations at practitioner events, media coverage and time requests from industry (Aguinis et al., 2014), but there is a catch here. It would of course be ideal if all researchers published both high quality academic journal articles and managerial reports, as well as engaged in a multitude of other dissemination forms (MacCarthy et al., 2013). However, it is often so that the one who writes highly influential journal articles is not the same person who meaningfully influences practitioners. It is actually more likely that some individuals are more influential in either internal or external impact (Aguinis et al., 2019). Nevertheless, there is still a basic necessary condition with respect to the scientific knowledge itself: in order for knowledge to be useful when disseminated, it has to be both relevant and rigorous. It is good science that makes a difference (Antonakis, 2017).

The results from Study I (Paper A) can be directly used by practitioners as input to strategic development of maintenance. The projections and scenarios support the defining of long-term strategies for designing, structuring and developing maintenance practices that fit in digitalised manufacturing. Moreover, the results help to stimulate new perceptions and behaviours of maintenance managers. In particular, this enables managers to see the bigger picture of digitalisation so as to evaluate and potentially rethink their internal and external environment. It helps mangers to consider things that they would otherwise ignore, and this is bound to make them more prepared for the disruptiveness of digitalised manufacturing. The results from Study I have already been independently used by multiple manufacturing firms as input to strategic development of their maintenance organization, presented at numerous practitioner events (e.g. practitioners' communities, fairs and top management meetings in industry), deployed in industry education as the basis for examination, covered in practitioner media, and requested for interviews from industry.

Above all, the results from Study II (Paper B & C) bring clarity to practitioners. Practitioners and policy-makers struggle with getting to grips with digitalisation and specifying how to exploit its opportunities and overcome its challenges. The study sorts out the confusion by providing an understandable, holistic and action-inspiring conceptualization of Smart Maintenance. Practicing maintenance managers can now clearly understand what the key goals should be for the organization, what the barriers are to its implementation, and what the expected effects are. Policy-makers can use the results as guidance for deploying initiatives aimed at elevating the use of Smart Maintenance and/or remove barriers to its adoption. In fact, the results shape the conversation between scholars and practitioners with respect to maintenance in digitalised manufacturing. This makes it possible for researchers and practitioners to speak the same language, work towards the same goals, and share ideas and experiences with one another. The results from Study II have already been presented at various practitioner events (even to the point where invitations exceed presentation capacity), as well as to top management boards of multi-site industrial corporations, included in industry education, and even served as the mediating knowledge for enabling economic transactions between buyers and suppliers within industrial maintenance.

The measurement instrument developed in Study III (Paper D) makes it possible for practitioners to assess, benchmark and longitudinally evaluate Smart Maintenance in their organization. Using the instrument therefore serves to develop evidence-based strategies for implementing Smart Maintenance in individual plants, as well as stimulating the sharing of knowledge, experience and best-practices between plants. It is a classic saying that what does not get measured does not get managed, and Smart Maintenance is now measurable and manageable. Benchmarking tools are in general really effective in influencing practice (MacCarthy et al., 2013), and the development of a valid and reliable instrument ensures that the results accurately reflect the proposed concepts (MacKenzie et al., 2011). The benchmarking insights obtained from the empirical pilot in Study III have already been used to create roadmaps for transformation towards Smart Maintenance in both discrete- and continuous manufacturing plants, as well as to develop new digitalisation services within industrial service firms and consultancies.

5.8 HAS THERE BEEN ANY PROGRESS?

Lifting the level of abstraction from each individual study to the overall, a few key reflections can be made. Here, it is most useful to reflect upon the overall progress of the scientific quality from Study I to Study III. After all, a PhD is an education – a process that produces the knowledge, skills, abilities and other characteristics needed to conduct high quality scholarly work. In particular, three things characterize the development from Study I to Study III. Together, they can be summarized as: I am a lot better now than I used to be.

Firstly, there is increased skill in careful data analysis, both qualitatively and quantitatively. While Study I followed several general qualitative principles, such as constant comparison, Study II was executed with a drastically higher level of qualitative rigor. Similarly, while Study I utilized basic descriptive statistic and regression analysis, Study III deployed a more holistic statistical approach using multiple techniques such as ANOVA, PA and EFA. After these five years, I see myself as a bilingual, maybe even multilingual, researcher. By that I mean the ability to design and execute both qualitative and quantitative research, as well as to use multiple methods to collect, analyse and interpret various types of empirical data. This has enabled me to conduct useful empirical research that has an impact on both the academic community and the practice of industrial maintenance management. In part, this development can be attributed to my continuously growing interest in research methodology. I do not by any means classify myself as a methodology expert, but I am fairly confident that my interest and willingness to learn is above average.

Secondly, there is a more structured and strategic use of theory, as well as a shift in the theories, literature and topics that inspire me. While Study I incorporated existing literature in the study, as well as compared the results to present knowledge, Study II and III used general theories as guiding principles to design the work and lenses to interpret data. That is, actively *using* theory as a tool to conduct the research, rather than just comparing the results of the study to existing literature within the field. Moreover, comparing the theoretical background in paper A to that of papers B-D, as well as to the frame of reference in this thesis (Chapter 2), it is clear that my sources of inspiration have shifted. In the early years of my PhD education, I largely focused on reading field-specific literature about maintenance, as well as closely related manufacturing literature. Today, I am much more inspired when I read papers from organizational science, strategic management or economics. I find it particularly motivating to make use of and combine the insights of multiple disciplines to solve problems within my own domain.

Thirdly, and finally, more emphasis is put on the very nature of empirical research. Everyone knows that ‘what goes around comes around’, and this becomes obvious if you reverse-engineer the empirical research approach. If the end result is theory capable of prescribing successful actions, then theory needs to be tested. In order to test theory, one needs measures that corresponds well to the concepts that make up the theory. To avoid deficient and contaminated measures, one needs clearly defined concepts and descriptions of their content domain. Such information can only be obtained by going out and observing phenomena that are relevant to practice. In other words, it is probably safe to bet that hard work in the beginning is going to pay off in the end. Getting it right requires an overall understanding of empirical research; its opportunities and pitfalls in every step - from asking the right questions to designing and executing studies that provide the right answers. While I have always had a strong focus on practical real-world problems, I have gradually increased my appreciation for the “higher level purpose” of building, elaborating and testing theories that explain empirical phenomena. There is indeed much truth to the classic quote that “nothing is quite so practical as a good theory” (Van de Ven, 1989).

5.9 FUTURE WORK

With respect to my individual future work, the next step is clear: large-scale studies aimed at further confirming the validity of the measurement instrument, followed by testing the empirical propositions with respect to Smart Maintenance; for example, testing the concept structure of Smart Maintenance, as well as testing the relationships between Smart Maintenance and performance. Moreover, there is still plenty of room for further theory building and theory elaboration with respect to Smart Maintenance; for example, building more theory regarding micro topics such as institutional work and individual-level performance outcomes, or refining elaborations of specific relationship between contextual factors and Smart Maintenance (see discussion sections in paper B &C).

With respect to collective future work, this thesis offers the opportunity to make a collaborative appeal to the research community of industrial maintenance management. Solving the puzzle of Smart Maintenance through empirical research requires hundreds of scholars working together to build, elaborate and test ideas that solve practical problems. A field that effectively unites the distributed and diverse work of the many will undoubtedly outweigh the performance of any single individual. When the scientific interest for a topic grows, scientific communities tend to form around a phenomenon, a theory or a class of problems. Attracting scientists with shared interests but different knowledge, backgrounds and experiences enables an entire community to reflect and work towards a comprehensive understanding of variable-rich, complex and fast-changing phenomena (Von Krogh et al., 2012). I hope that this thesis can act as a springboard for this development.

With respect to the future work of practitioners, the scenarios for maintenance in digitalised manufacturing, as well as the conceptualization and operationalization of Smart Maintenance, enables the adoption of Smart Maintenance in manufacturing plants. This is expected to stimulate the development of the industrial maintenance profession to advance from being a low-priority sustainer of the technical status quo to being a leading enabler of high performance manufacturing in digitalised manufacturing. In the best of worlds, I would like to see failure-free production, which in turn will contribute to the realization of economically, ecologically and socially sustainable production systems that play a key role in creating a sustainable, prosperous society.

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CONCLUSIONS

To ensure high performance manufacturing in digitalised environments, this thesis has contributed to achieving a holistic understanding of Smart Maintenance. Specifically, future scenarios for maintenance in digitalised manufacturing have been developed, which enable managers to see the bigger picture of digitalisation and help them become more prepared for the disruptiveness of digitalised manufacturing. Moreover, a rich, understandable and action-inspiring conceptualization of Smart Maintenance has been achieved. Smart Maintenance is defined as ‘an organizational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies’, and consists of its four underlying dimensions: data-driven decision-making, human capital resource, internal integration and external integration. In addition, a contingency model of Smart Maintenance, contextual factors and performance have been specified, which serves as an empirical research agenda for industrial maintenance management. Finally, an empirical measurement instrument for Smart Maintenance has been developed, making it possible to assess, benchmark and longitudinally evaluate Smart Maintenance in manufacturing plants, as well as test its impact on performance.

Together, this holistic understanding enables the adoption of Smart Maintenance and thereby ensures high performance manufacturing in digitalised environments. This encompasses the realization of production systems that are economically, environmentally and socially sustainable, and capable of contributing to a sustainable, prosperous society.

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